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The sensing resources represent an important source of information on which the Command & Control (C2) process bases most of its reasoning. Therefore, a major prerequisite to the success of the whole C2 process is the effective use of these scarce and costly resources. This is the problem of sensor management that has to do with how best to manage, coordinate and organize the use of sensing resources in a manner that synergistically improves the process of data acquisition and ultimately those of perception and comprehension, i.e., the situation awareness of the decision maker. Conscious of the important role sensor management has to play in modem Command and Control systems, the Situation Analysis Support Systems (SASS) Group of the Decision Support Systems (DSS) Section at Defence Research & Development Canada (DRDC) - Valcartier is currently studying advanced sensor management concepts and applications, to increase the survivability of the current Halifax and Iroquois Class ships, as well as their possible future upgrades. The objective of the reported work is twofold i) to present, in detail, the different sensor management problems and the requirements for their solutiOn ii) to demonstrate, through the target tracking application, the benefits that can be gained by the adaptive management of the available sensors.

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Sensor management in the context of the integration of sensors and weapons

Abder Rezak Benaskeur
Decision Support Systems Section

Defence Research & Development Canada - Valcartier
Technical Report
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Abstract (U)

The sensing resources represent an important source of information on which the Command & Control (C^2) process bases most of its reasoning. Therefore, a major prerequisite to the success of the whole C^2 process is the effective use of these scarce and costly resources. This is the problem of sensor management that has to do with how best to manage, coordinate and organize the use of sensing resources in a manner that synergistically improves the process of data acquisition and ultimately those of perception and comprehension, *i.e.*, the situation awareness of the decision maker. Conscious of the important role sensor management has to play in modern Command and Control systems, the Situation Analysis Support Systems (SASS) Group of the Decision Support Systems (DSS) Section at Defence Research & Development Canada (DRDC) - Valcartier is currently studying advanced sensor management concepts and applications, to increase the survivability of the current Halifax and Iroquois Class ships, as well as their possible future upgrades. The objective of the reported work is twofold i) to present, in detail, the different sensor management problems and the requirements for their solution ii) to demonstrate, through the target tracking application, the benefits that can be gained by the adaptive management of the available sensors.

Résumé (U)

Les capteurs représentent une importante source d'information pour les systèmes modernes de commandement et contôle (C^2). Afin de maximiser l'efficacité des systèmes des C^2, ces capteurs doivent être gérés. La gestion des capteurs concerne la coordination et l'organisation de l'usage de ces ressources dans le but d'améliorer le processus fusion des données. Conscient du rôle que la gestion des capteurs aura à jouer dans les systèmes modernes de commandement et contrôle, le groupe des systèmes d'aide à l'analyse de situation (SAAS) de la section des systèmes d'aide à la décision (SAD) à Recherche et Dévelopment pour la Défence Canada (RDDC) - Valcartier explore actuellement des concepts avancés de gestion et contrôle des capteurs, ainsi que leur possible application aux capteurs de la frégate canadienne. Le travail présenté dans ce rapport couvre deux aspect: i) la présentation du problème de la gestion des capteurs sous ses differentes facettes; ii) illustrer, par le problème du pistage des cibles, le gain que peut procurer une gestion efficace des capteurs.

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Executive summary (U)

The sensing resources represent an important source of information on which the Command & Control (C^2) process bases most of its reasoning. Therefore, a major prerequisite to the success of the whole C^2 process is the effective use of these scarce and costly resources. This is the problem of sensor management and control. Sensor management has to do with how best to manage, coordinate, and organize the use of the sensing resources in a manner that synergistically improves the process of the data acquisition and ultimately those of perception and comprehension, that is, the situation awareness of the decision maker.

Sensor management is about decisions on alternate sensing strategies. The development of such sensor management strategies is driven by many factors such as information requirements and the priority of the events. Based on the available contextual information, the sensor management system develops options for collecting further information, allocates and directs the sensors towards the achievement of mission goals and/or tunes the parameters for the real-time improvement of the sensing process. The sensor management system must allocate the available sensors to those tasks that maximize the effectiveness of the whole sensing process, while reducing the workload of the human operator. The statement of the sensor management problem assumes the existence of either a multi-mode/multi-function/agile sensor and/or a set of cooperative sensors.

Several concepts of sensor management and control have been investigated and reported in the literature. While most of the reported applications focus mainly on the effective use of agile and/or multi-function resources, such as the Electronically Scanned Antenna (ESA), our work must take into consideration the Canadian Patrol Frigate current and possible future sensor suites. Therefore appropriate concepts need to be defined and investigated. The objective of the reported work is however twofold: i) to present in detail the different sensor management problems and the requirements for their solution; ii) to demonstrate the benefits that can be gained by the adaptive management of the available sensors.

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Sommaire (U)

Les capteurs représentent une importante source d'information pour les systèmes modernes de commandement et contrôle (C^2). Afin de maximiser l'efficacité des systèmes des C^2, ces capteurs doivent être gérés. La gestion des capteurs concerne la coordination et l'organisation de l'usage de ces ressources dans le but d'améliorer le processus fusion des données.

La gestion des capteurs a trait aux décisions relatives au choix des stratégies surveillance et pistage. De nombreux facteurs régissent la pise sur pied de stratégies de gestion des capteurs, comme le besoin en information et la priorité des évènements. Sur la base de l'information contextuelle disponible, le système de gestion permet de collecter davantage de données, d'assigner et orienter les capteurs en vue d'atteindre les objectifs de mission, et de régler les paramètres afin d'obtenir une amélioration en temps réel. Le système de gestion des capteurs doit affecter les capteurs disponibles aux tâches permettant de maximiser l'efficacité de l'ensemble du processus de détection et pistage, tout en diminuant la charge de travail de l'opérateur. L'énoncé du problème de gestion des capteurs suppose l'existence de capteurs agiles/multi-modes/multi-fonctions ou d'un ensemble de capteurs en coopération.

Plusieurs concepts de gestion des capteurs ont été étudiés et documentés. Comme la plupart des applications présentées ont essentiellement pour but d'assurer l'utilisation efficace des ressources multi-fonctions/agiles, on doit tenir compte des capteurs actuels et futurs de la frégate de patrouille canadienne. Il faudra par conséquent définir et investiguer les concepts appropriés.

Le travail présenté dans ce rapport couvre deux aspects: i) la présentation du problème de la gestion des capteurs sous ses différentes facettes; ii) illustrer, par le problème du pistage des cibles, le gain que peut procurer une gestion efficace des capteurs.

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1. Introduction

The essence of the Command & Control (C^2) process is acquiring information, assessing how this information affects current activities, determining a course of action and directing the implementation of this action. This process is well schematized by the Boyd's Observe-Orient-Decide-Act (OODA) loop (see Figure 1).

Therefore, an important prerequisite to the success of the whole C^2 process is the effective use of available sensing resources, which defines the problem of sensor control and management. This explains why the problem of management of the sensors, involving tuneable and multi-mode sensors, configurable sensor suites or constraints in communication bandwidth and sensing/processing resources, has become increasingly common in C^2 applications.

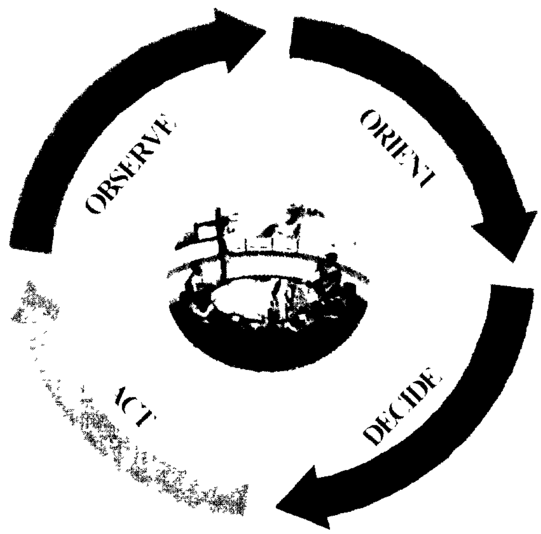


Figure 1: *OODA loop*

Sensor management, in the light of situation analysis, has to do with how best to manage, coordinate and organize the use of scarce and costly sensing resources, usually in a multi-sensor system, in a manner that synergistically improves the process of data acquisition, and ultimately those of perception and comprehension [1, 2]. It ultimately reduces to making decisions regarding alternate sensing strategies. The development of such sensor management systems is driven by many factors such as information requirements and the priority of events. It can be considered as a part of the process refinement system (*i.e.*, the JDL's Level-4 data fusion) that is concerned with the optimization of the whole fusion process (see Figure 2). These considerations extend beyond the topics gathered under the "sensor fusion" paradigm (*i.e.*, Level 0 to 3 of the JDL model). The fusion problem involves the effective exploitation of data from a

collection of sensors, under the assumption that the sensor configuration is defined beforehand. Fowler [3] affirms that

> *"One of the grabbiest concepts around is synergism. Conceptual application of synergism is spread throughout military systems but is most prevalent in the multi-sensor concept. This is a great idea provided the input data are a good quality. Massaging a lot of crummy data doesn't produce good data; it just requires a lot of extra equipments and may even reduce the quality of the output by introducing time delays and/or unwarranted confidence."*

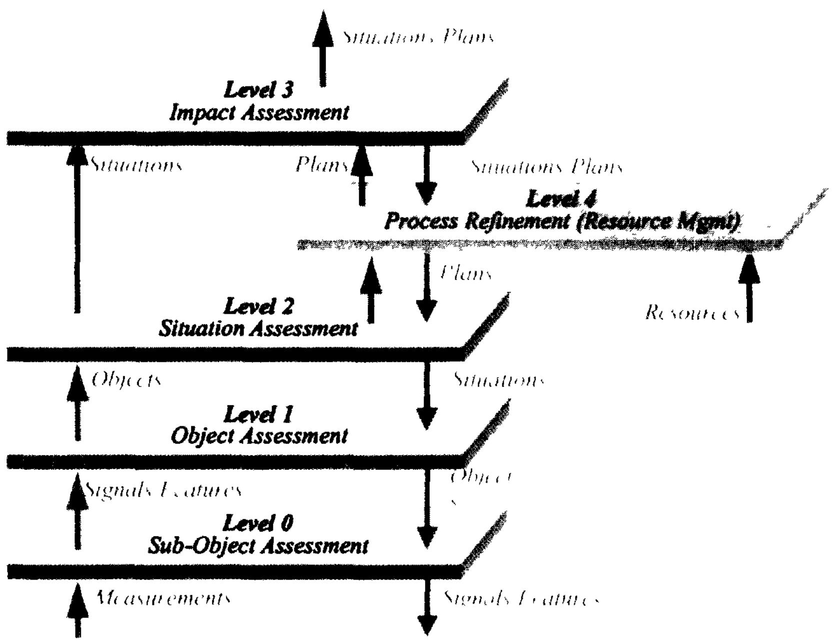


Figure 2: *JDL model*

It is clear that the data fusion system cannot be of any help if the data at its input does not contain a minimum amount of exploitable information, and it is the aim of the sensor management to improve the quality of the data provided as an input to data fusion systems. One approach to contribute to such an improvement is through the control and management of the sensors and/or the groups of sensors to allow for an optimal achievement of the sensing tasks (*i.e.*, improving the perception and, consequently, the situation awareness). This sensor management problem is well defined by Greenway [4] as

> *"Given limited sensing and/or processing resources, further decisions have to be made about how to allocate them so as to maximize the effectiveness of the*

overall data fusion system. This is the essence of the sensor management problem."

Hence, based on the newly available contextual information, the sensor management system develops options for collecting further information, allocates and directs the sensors towards the achievement of the mission goals and/or tunes the parameters for the real-time improvement of the sensing/fusion process. Whenever there are insufficient resources to perform all of the desired tasks, the sensor management must allocate the available sensors to those tasks that maximize the effectiveness of the whole sensing/fusion process, while reducing the workload of the human operator. The statement of the sensor management problem assumes the existence of one or more of the following (manageable) situations

1. multi-mode/agile sensors,
2. multi-function sensor,
3. suite of multiple sensors on a common platform and/or
4. set of geographically distributed sensors/platforms.

As it is clearly presented in Chapter 2, for each of the above given situations, a set of management problems can be identified. Mathematical foundations can then be developed for framing and addressing the questions related to these problems.

Conscious of the important role that sensor management has to play in modern Command and Control systems, the Situation Analysis Support Systems (SASS) Group of the Decision Support Systems (DSS) Section at Defence Research Establishment Valcartier (DREV) is currently studying advanced sensor management concepts and applications. Several concepts of sensor management and control have been investigated and reported in the literature. While most of the reported applications focuse mainly on the effective use of agile and multi-function resources, such as the Electronically Scanned Antenna (ESA), our work must take into consideration the Canadian Patrol Frigate actual and possible future sensor suites. Therefore appropriate concepts need to be defined and investigated. The objective of the reported work is twofold

1. to present in detail the different sensor management problems and the requirements for their solution.
2. demonstrate the benefits that can be brought by the adaptive management of the available sensors.

This report is organized as follows. In Chapter 2, the different management tasks are presented. This defines the various problems that the management system will have to handle. Requirements for the solution of these problems are detailed in Chapter 3, while an illustrative application is presented in Chapter 4 to show the benefit that can be

gained by using adaptive management policies. This application concerns dynamic sensor allocation for the tracking of a set of targets. Some concluding remarks are given in Chapter 5.

2. Management tasks

Sensor management aims at studying and implementing policies that improve and optimize the on-going sensing process and, consequently, the data fusion process. The management here essentially concerns the moding, the pointing and/or the controlling of the available sensors to allow for an optimal achievement of the sensing objectives, namely, improving the perception while reducing the operator workload and resource consumption.

The management system closes the loop over all of the sensing resources and, based on the dynamically available contextual information, it develops sensing options. As stated in Chapter 1, the formulation of the sensor management problem assumes the existence of one or more of the following scenarios

1. multi-mode/agile sensors,

2. multi-function sensor,

3. suite of multiple sensors on a common platform and/or

4. set of geographically distributed sensors/platforms.

These different situations define a kind of a hierarchy for the management problems. This decomposition allows for efficiently tackling all of the questions related to sensor management, by subdividing them into many smaller sub-problems that can be considered separately.

The resulting decomposition of the management tasks is described below, and is summarized by Figure 3. It considers two main situations:

1. Single-sensor problem : includes situations 1 and 2 of the above given list. This concerns the management of a single multi-mode, an agile or a multi-function sensor.

2. Multi-sensor problem : includes situations 3 and 4, and implicitly situations 1 and 2. It concerns the management of a set of sensors that can be located on the same platform or distributed over a set of platforms.

These two main classes of problems are discussed below.

2.1 Single-sensor problem

Consider the situation of a single sensor on a single platform. The following represents the different levels of management that can be performed on the unique available resource.

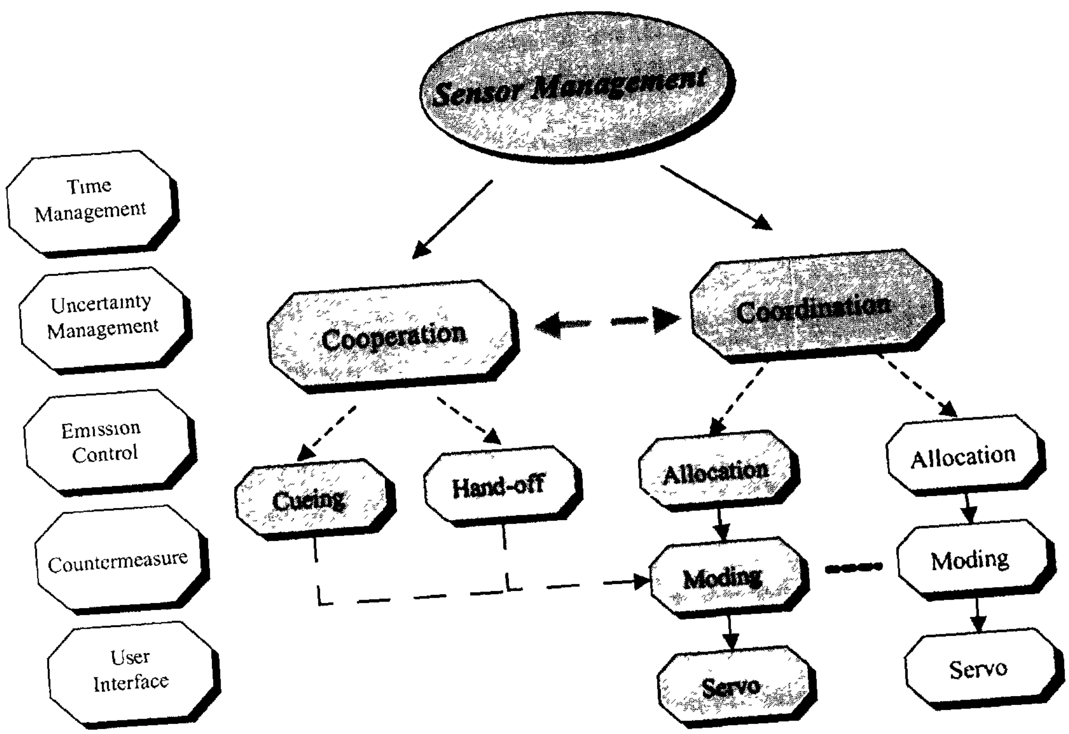


Figure 3: *Sensor management tasks*

2.1.1 Servo-control

This level of management concerns the servo-control aspects. Since it deals with hardware components, this control problem can be efficiently tackled through classical control theory. The role of the controller is to ensure that the desired low-level goals are being achieved with the desired level of performance. An example is given by the control system that ensures that the radar antenna is being accurately pointed towards the predicted bearing of the target (see Figure 4).

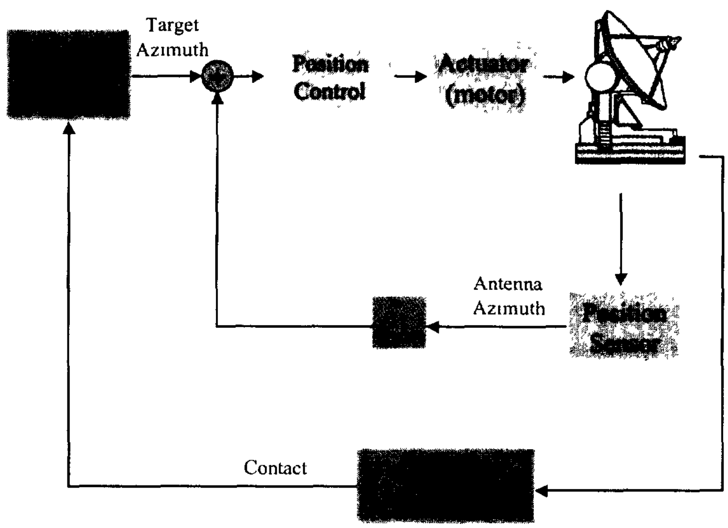


Figure 4: *Radar servo-control*

2.1.2 Moding

The moding is another management task that also concerns single sensors. The mode management and control implicitly assume the existence of several sensing strategies, such as those provided by agile or multi-mode sensors. The operating mode and/or configuration for the considered sensor should therefore be selected at run-time to achieve the best performance.

2.1.3 Allocation

Another decision problem, that needs to be tackled by sensor management, is where the unique available sensor should be pointed to best achieve the sensing objectives. For the target-tracking problem, this may for instance include pointing the sensor to update tracks (*i.e.*, to cover the already detected targets) and/or search for new ones (undetected targets) that enter the volume of interest. The pointed area may be selected based on the predicted value of

the future target position. This boils down chiefly to finding the best trade-offs in the presence of conflicting goals. Note that latencies in the sensor tasking and processing may result in missed opportunities to maintain tracks and classify targets.

The above described allocation task can be regarded as an information gathering problem. This essentially concerns a decision-making problem about what information needs to be gathered from the environment, and what actions need to be taken to best gather it. Such actions may be taken to focus on the most important elements in the environment in order to reduce the uncertainty in the available information, to collect missing information and/or to confirm the tactically inferred information.

It is worth noting that very important issues for the sensor allocation problem are the target ranking/priority assignment and the sensor capability/status establishment. The allocation optimization criterion must be a function of both of the performance of the sensor against the targets and the priorities of the targets.

2.1.3.1 Target priority

Some targets are more important than others. An example of a high priority situation is an unknown target approaching at a high speed. When the importance (or threat) level of each target object is known, it is possible to select the appropriate action. As a result, the targets with a higher priority will benefit from more attention than the others (*e.g.* will be revisited more frequently than the others). The targets may, for instance, be ranked, so the sensor can be allocated to the targets on the basis of threat lethality. The individual needs and priorities may be assigned manually by the operator, locally from the track information (Level 1 Data Fusion), or from the inferred/anticipated information (Level 2 & 3 Data Fusion).

2.1.3.2 Sensor capability

As mentioned by Waltz et al. [5], prior to their assignment alternatives, the ability of the available sensing resource must be established. The ability may be defined in terms of the availability (failure/businesses) and capability of the sensor against the threat.

2.2 Multi-sensor problem

The single sensor situation being a special case of the multi-sensor situation, all of the above cited management tasks are also encountered in the multi-sensor case.

Nevertheless, other management problems that are specific to the multi-sensor case, may arise. These mainly concern the inter-sensor cooperation/coordination tasks (see Figure 3).

2.2.1 Coordination

Decisions need to be made about how the available sensors should be allocated to gather the most valuable information. The available (limited) sensors must be partitioned among the tasks (targets) in accordance with the individual needs/priorities of these tasks. This is known as the pairing problem (the distribution of the sensors or the sensor combinations across the targets, *i.e.*, with which sensor or sensor combination).

2.2.2 Cooperation

The management of the sensors may require that different sensors cooperate to acquire measurements on a common target. This, for instance, consists in dynamically tasking some sensors to fill the coverage gaps of other sensors, and therefore provide relevant observations in the areas of tactical interest. The two primary cooperative functions are the cueing and the hand-off.

The cueing is the process of using the detections (*i.e.*, contact-level cueing) or tracks (*i.e.*, track-level cueing) from a sensor A to point another sensor B towards the same target or event. The hand-off occurs when sensor A has cued sensor B for transferring the surveillance or the fire-control responsibility from A to B. Hence, the response time/performance of sensor B may be improved by providing it with the detections, the measurements or the tracks from sensor A with different characteristics. This may also be used to ensure a continuity of the tracking, when a tracked target passes out of the (spatial/temporal) coverage of a sensor A to enter the one of a sensor B.

2.3 Implicit management tasks

Besides the above-cited tasks, several other issues will need to be addressed by the sensor management system. These represent the tasks induced by the constraints imposed by the environment, the doctrines and/or the technology. Below are presented some of the most important aspects to be considered.

2.3.1 Time management

Of prime importance for any management system is the ability to ensure synchronization and real-time operations, that is, responding quickly to rapidly changing situations (environment and/or goals). The sensor management module is often called upon to respond to high data rates and

time-critical requirements under severe limitations. These constraints militate against high fidelity and force into many trade-offs.

2.3.2 Uncertainty management

The sensor management behavior must degrade gracefully in the presence of increasing uncertainties. Since it often operates on the basis of incomplete, inaccurate, missing and/or misleading information, the sensor management should make the best use of the accurate pieces of information it possesses. An internal model of uncertainty (probability, possibility/fuzzy sets and/or belief) must therefore be used to obtain a consistent measure of the uncertainty.

2.3.3 Emission control

Active sensing equipment such as radars may betray their existence, by emitting energy, and therefore increase the vulnerability of the whole system. The use of such sensors thus needs to be minimized to control their emission when/where there is a strong requirement on a "silent" radar work to achieve the Low Probability of Intercept feature (so called LPI radar). The optimization criterion (to be minimized) may be the detectability and/or the identification of our own sensor suite. Controlling the emitted power, its duration and the spatial coverage of the active sensors can be used to reduce the emission.

2.3.4 Countermeasure management

This aims at reducing the effects of the countermeasures (deception, jamming, exploitation) on the performance of the sensor suite. This rather concerns the Electronic Counter-Counter-Measure (ECCM) that aims at taking actions to protect sensors from any effects of friendly or enemy employment of an electronic warfare that degrades, neutralizes, or destroys the friendly combat capability.

2.3.5 Operator interface

Since, in C^2 context, the ultimate authority and responsibility belong to the human operators, the management system must allow taking into account their commands and preferences. Therefore, the sensor management system must provide an interaction interface with the operators.

3. Management requirements

Handling the sensor management problem presumes that the required performance of the closed-loop system can be specified quantitatively to allow the definition of the management objective. A performance index can then be calculated (or measured) and used to evaluate the system's performance (*i.e.*, the deviation from the desired behavior). On the basis of this deviation, actions are undertaken to make the system meet the specification. The cycle "performance evaluation/action selection and execution" continues on during the lifetime of the system. The specifications can also be modified at run-time; but this is not required to be done periodically and can be performed only on an aperiodic basis.

Hence, of a major importance to solve any management and control problem are the following tasks

1. Goal specification
2. Performance evaluation
3. Action selection

These tasks, often performed by the human operator, need to be addressed, either partly or entirely, by the sensor management module in a closed-loop operating mode.

3.1 Goal specification

Generally, specifications can be divided into two categories: performance specifications and robustness specifications. Both need to be explicitly specified to achieve the management goals. Although the boundaries between the two cannot always be clearly specified, the performance specifications describe the desired response of the nominal system (*i.e.*, in absence of uncertainty). The robustness specifications limit the degradation of the performances in the presence of uncertainty that may come under various forms, as uncertainties in the system models (also known as parametric uncertainties) and/or constraints on the admissible actions. Another important requirement is to keep the management effort (time and resources consumption) minimal. The latter often acts rather as a constraint in the problem statement.

The specifications depend however on how the problem is modeled. In the literature, there are mainly three main approaches. The first formulation presents sensor management as a control problem; the second uses an optimization formulation, while the third is based on decision theory and related utility concepts.

3.1.1 Sensor management as a control problem

The sensor management can be stated as a control problem [6, 7]. The user specifies, in this case, the desired level of performance (or the reference

trajectory) defining the management policy that the closed-loop system tries to achieve. The difference between this reference trajectory and the measured level of performance provides a good index of the system actual behavior with respect to the desired behavior (see Figure 5).

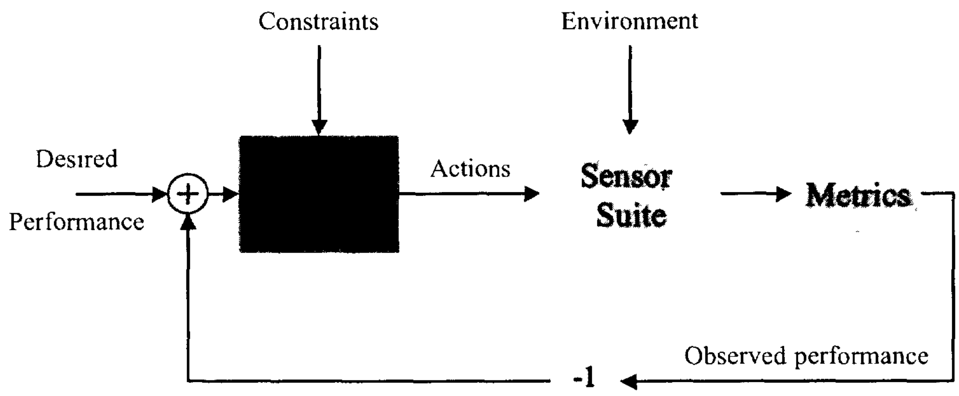


Figure 5: Sensor management as a control problem

This index is used as an action selection (or control design) basis to reduce, and/or maintain as small as possible, any observable discrepancy.

3.1.2 Sensor management as an optimization problem

Sensor management can also be modeled as an optimization problem [8–11]. In such a case, rather than specifying a desired performance level, the user defines a cost function that, once minimized by the management module, leads to the most desirable outcome. This minimization would lead to the best trade-off between the sensing action payoff and the associated costs. An example of such an optimization formulation is illustrated in Figure 6.

The objective here is to maintain the gradient of the cost function as close to zero (optimum for the function itself) as possible. One can notice that this formulation is very similar to the control case of Figure 5, where the objective is to maintain the discrepancy between the desired level of performance and the observed one as close to zero as possible. The difference lies here mainly in that the optimal performance level is not known explicitly as it was in the case of the control formulation.

3.1.3 Sensor management as a decision problem

When the sensor management is modeled as a decision problem, there is no specified desired level of performance. As in the case of the optimization

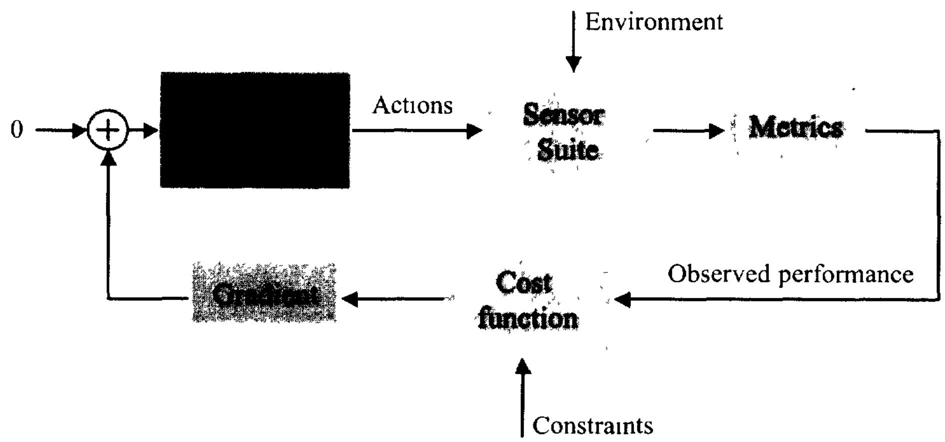


Figure 6: Sensor management as an optimization problem

formulation, the objective is to choose the action that maximizes some quantity, known as the expected utility function. Therefore, what is specified here is the utility (*i.e.*, the benefit) of executing a given action in a given situation (defined by events). The best solution is the one that offers the highest utility, that is, the best achievable performance.

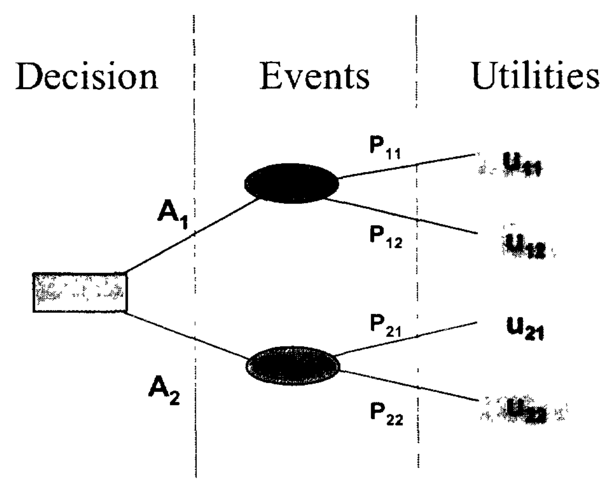


Figure 7: Sensor management as a decision problem

In Figure 7, A_1 and A_2 are the two possible actions to choose from, P_{ij} are probabilities of the possible outcomes that depend on both the action selected and the environment state and u_{ij} are the utilities associated with each situation defined by a pair action/state. The aim of the decision problem here

is to select the action that offers the maximum expected utility. The latter is given for the two possible actions by

$$EU_1 = p_{11}u_{11} + p_{12}u_{12} \quad (1)$$
$$EU_2 = p_{21}u_{21} + p_{22}u_{22} \quad (2)$$

3.2 Performance evaluation

As can be noticed from the previous section, central to the management problem is the performance evaluation, or metric, aspect. Using the available resources, candidate solutions are constructed. These alternatives usually provide a large number of possible combinations; a subset of candidates is intelligently selected to represent the primary categories of alternatives [5]. The criteria for evaluating these alternatives must be defined quantitatively in the form of measures of merit that can be determined for each candidate. These measures must allow discrimination between alternatives [5].

Given the knowledge of the current state of the environment and the objective, choosing the optimal management policy therefore boils down to finding a metric that serves as an action selection basis, or utility function (to use the decision theory terminology). Such a utility function is required to grade the benefits from the different possible actions, so that the "best" solution can be chosen. For instance, in the data fusion context, the information update paradigm may lead to an intuitive method of addressing the metric selection problem. One of the most used metric is the Fischer Matrix that concerns track uncertainty in the Level-1 Data Fusion (L1DF). Some interesting L1DF-related metric are discussed below.

3.2.1 Detection metrics

In the context of surveillance and tracking, the target detection is the process of determining the presence of a target in the volume of interest. This corresponds to a decision problem of the form

$$H_0 \quad : \quad \boldsymbol{X} = \boldsymbol{N} \quad (3)$$
$$H_1 \quad : \quad \boldsymbol{X} = \boldsymbol{S} + \boldsymbol{N} \quad (4)$$

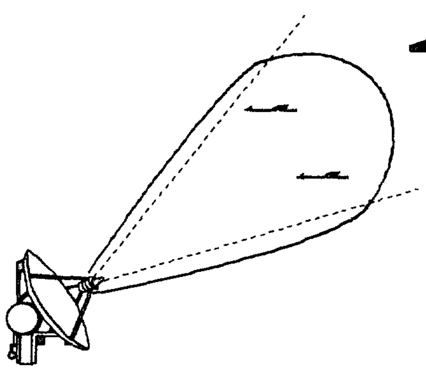
where $\boldsymbol{N}$ represents a zero-mean normal noise, that is,

$$\boldsymbol{N} \sim \mathcal{N}(\boldsymbol{0}, \sigma^2 \boldsymbol{I}) \quad (5)$$

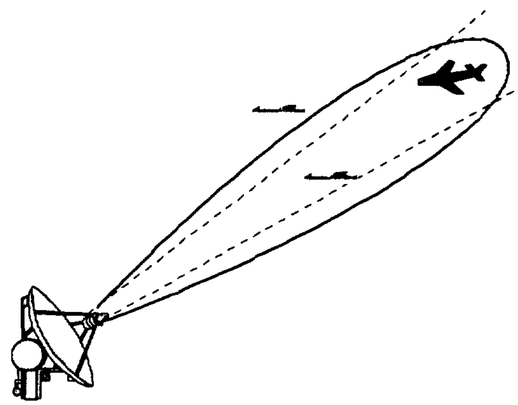
and $\boldsymbol{S}$ a signal of known energy, *e.g.* $\|\boldsymbol{S}^2\| = 1$ for simplicity. A widely spread approach to tackle this problem is to compare the incoming signal power to a threshold typically set, so that the probability of false alarm (P_{FA}) remains constant. Detection occurs (*i.e.*, H_1) each time the received power exceeds the selected threshold. For a given threshold setting, the probability of target detection (P_D) will generally be a complex function of the sensor capabilities, the target size, the sensor/target geometry and the physical

environment. The threshold value, and resulting P_D and P_{FA}, should be selected taking into account its effect on the overall tracking system performance. At the detection stage, the performance measures are the probability of false alarm (P_{FA}), that is to be minimized, and the probability of target detection (P_D), that is to be maximized.

In the presence of detectors that offer multiple operating modes (*e.g.* multiple mode search radars) search strategy needs to be defined to optimize the detection task. The different operating modes differ by their different detection performance (*i.e.*, the probability of detection) and the geographical coverage (see Figures 8 (a) & (b)). Broad search modes offer a large geographical coverage, but a low detection performance, while focused modes improve the detection performance at the expense of a smaller geographical coverage.



(a) Broad search mode



(b) Focused search mode

Figure 8: *Multiple mode search radar*

The management problem (*i.e.*, moding) consists then in developing the search policy that offers the best trade-off in using the available modes. To address this problem, [12] uses a Bayesian approach to select the optimal search mode for the maximization of the a posteriori detection probability. Two properties of the radar allow the definition/selection of such modes.

3.2.1.1 Beam width

Different search modes can be obtained by controlling the radar beam width. A large beam width covers large sectors, but at the expense of a low spatial resolution and a low probability of detection (due to the low SNR resulting from the antenna low

gain). On the other hand, a narrow beam increases the probability of detection, but only over a small area.

An optimal search strategy may consist in alternating the use of the available search modes to maximize the probability of detection over the largest possible area, or cover the whole volume of interest with the highest possible probability of detection.

3.2.1.2 Beam agility

Another approach to obtain a variable search performance is offered by the so-called agile beam radars. The beam can be positioned in any time and direction within the volume of interest. This property is made possible by the electronically scanned phase array antenna of such radars. Hence, based on the contextual information, the radar beam can be pointed towards the region where detection is most likely expected to happen.

If the expected detection does not occur, additional looks may be required. These additional looks can be quickly obtained by backscanning, if the antenna has been repositioned. Since the pulse integration improves the P_D by reducing noise variance, the longer the radar stares at the target, the higher will be the SNR and P_D. Therefore, the time spent on the target during the illumination can also be controlled in order to improve detection performance. Such a control of the time spent on the target is made possible by the agility of the radar beams. This property allows also the separation of the illumination from the search and track update functions.

3.2.1.3 Detection threshold

An even higher probability of detection may be obtained if the above-given mode selection approaches are combined with an adaptive setting strategy for the detection threshold. Based on the available information (*e.g.*, from higher levels of fusion), the threshold may be lowered over some specific areas (where undetected targets are expected) to increase the detection probability P_D, at a constant probability of false alarms P_{FA}.

Such an adaptive threshold setting policy is used in [13]. The proposed approach is based on the minimization of the expected discrimination gain (see the definition below) to optimize the detection. A similar work is reported in [14], where the objective is also to maximize the detection probability through an optimal management of the search effort.

3.2.2 Correlation metrics

Data association has to do with the problem of labeling measurements from different sensors and/or different times as corresponding to the same object or feature. This is a straightforward task in the presence of a single target and one maintained track. However, in complex environments involving multiple targets and multiple sensors, more elaborate strategies are required to decide which target report goes with a track. In this context, the probabilities of correct correlation P_{CC}, false correlation P_{FC}, and correct decision P_{CD} are important measures of the system performance [15].

The probability of a correct correlation P_{CC} is defined as the probability for each track of being associated with the correct measurement. Its value depends on the object density in the measurement space and on the average innovation standard deviation [16], which, in turn, depends on the measurement and the target state estimate accuracy. Analytically, the probability of a correct correlation P_{CC} is given by

$$P_{CC} = P_D P_{CC|D} \tag{6}$$

where, P_D is the probability of the detection of the target, and $P_{CC|D}$ is the probability of a correct correlation given that a detection occurred.

With respect to sensor management, little work has been reported in the literature on the direct use of the correlation metric as an action selection basis. An example of such a rare work is reported in [17], where the concept of discrimination gain (see the definition below) is used to minimize the error correlation between close targets.

The correlation performance may however be increased significantly by improving the discrimination power of the sensor suite (*i.e.*, spatial/temporal resolution). This can be obtained by pointing additional resources towards those regions where clusters of closely spaced targets are expected/detected.

3.2.3 Tracking metrics

The main objective of an ideally effective Level-1 Data Fusion (L1DF) system is to establish a number of clean, stable tracks that correspond exactly to the number of objects in the physical environment. This requires acquiring and maintaining unambiguous, stable tracks corresponding to the perceived population of the real objects within the volume of interest, and estimating the state of each tracked object. The effectiveness of countering an attack depends heavily on the accuracy and timeliness of the track information. This explains the large amount of work that aims at improving tracking performance through sensor management and control.

Since the primary goal of tracking is to reduce the uncertainty in the target's kinematic information, a metric is required to quantify the information gained by the sensing actions. A Kalman (or Kalman-like) filter [18] is often used for the estimation (fusion) of the target's state vector. Therefore, a natural metric for the tracking performance might be based on the error covariance matrix maintained by the Kalman filter, or other algorithm, such as the Interacting Multiple Model Kalman Filter [19]. Several alternative metrics were proposed in the literature. Some of the most used metrics are described below.

3.2.3.1 *Error covariance matrix*

The first use of the covariance matrix as a metric to address the problem of the sensor management was reported by [8]. The author uses linear programming techniques to determine sensor/track assignment, where the trace of the error covariance matrix maintained by a Kalman filter serves as cost coefficients in the objective function. The optimization problem corresponds then to the minimization of the variance of the states. The author applies optimization techniques to the one-stage-ahead allocation of information gathering resources to a set of externally prioritized targets. The management objective is that the most accurate available sensors track the targets with the highest priorities. Constructing pseudo sensors, which are combinations of the basic sensors, treats situations where more than one sensor may be assigned to the same target. The number of sensors (either actual or pseudo) is thus equal to $2^S - 1$, where S is the number of the individual (actual) sensors. The optimization problem consists in assigning the $2^S - 1$ combinations to the targets.

[20] uses an objective function that combines the trace of the error covariance matrix (the estimation performance) and the measurement cost (associated with the use of a specific sensor). The goal is to choose a sensing strategy (*i.e.*, a unique sensor) that minimizes the considered functional. Note that only one sensor is assigned to the target by a time period.

3.2.3.2 *Fisher information matrix*

The increase of the Fisher matrix P^{-1} is among the most used information measures. This corresponds to the reduction of the covariance matrix and is used in the literature in a very similar way to the covariance matrix discussed in the previous sub-section.

3.2.3.3 Entropy change

Another example of covariance matrix-based metric is given by the change of the entropy h that is defined as

$$h = E\left[-\ln(\hat{P}_{k+1|k+1})\right] \tag{7}$$

$$= \frac{1}{2}\ln((2\pi e)^n|\hat{P}_{k+1|k+1}|) \tag{8}$$

Such a metric is to be minimized. An equivalent formulation of the same problem is given by the maximization of the information measure

$$\imath = -h \tag{9}$$

$$= -\frac{1}{2}\ln((2\pi e)^n|\hat{P}_{k+1|k+1}|) \tag{10}$$

The entropy is used in [21] as an information metric to determine how to schedule sensors and the data processing, within a sensor management system. The authors consider the case of insufficient sensing resources with several targets being tracked. This consists in minimizing the error entropy that is given by the error covariance matrix maintained by the Kalman filter. In [22], the same measure of information was applied to the cueing problem within an automatic target recognition system.

The entropy change is used in [23] as an information theoretic measure that is combined with lattices of partially ordered sets to address the sensor management problem. The expected entropy change serves as an expected information gain, to determine an optimal order between search, track and identify for an ESA.

The entropy of the state vector is also used as a utility function in [2]. According to the authors, the use as a metric of such an entropy based information leads to a risk-averse behavior. This means that the calculation takes into account the probabilities associated with the acquisition of the information, which is not the case of the Fisher information metrics. The latter is risk-prone, since it considers only the information, which could be gained, regardless of the probability of acquiring it.

3.2.3.4 Discrimination Gain

Discrimination gain (or Kullback-Liebler information) [24] is another metric that is also related to the notion of information and entropy in probability distributions. This metric measures the

relative increase in information between two probability distributions (*e.g.*, before and after an action is undertaken).

A high discrimination gain (or low entropy) is associated with a sharply peaked (low variance) distribution. Used as a metric in the context of the sensor management, it defines the information gain brought by the sensing actions

$$G = \frac{1}{2} \ln \frac{|\hat{P}_{k+1|k}|}{|\hat{P}_{k+1|k+1}|} \tag{11}$$

where $\hat{P}_{k+1|k}$ is the covariance matrix prior to the measurement, and $\hat{P}_{k+1|k+1}$ is the covariance matrix after the measurement is performed.

To track multiple targets, the sensor allocation is considered in [25] as a linear programming problem, whose objective function to be minimized is based on the information increase defined by the discrimination gain. The problem formulation (*i.e.*, as a linear programming problem) is similar to that of [8]. But instead of the trace of the error covariance matrix used in the original article, the discrimination gain is used in [25] as a measure of sensor effectiveness. The considered optimization problem is one of assigning sensors to targets in such a way that the one step-ahead discrimination gain of the track set is maximized. In [26, 27], the expected gain is used to calculate the optimal order for search/detect/track tasks in the presence of multiple targets.

Since the expected discrimination gain based on the standard Kalman filter is insensitive to target maneuvers, an Interacting Multiple Model Kalman Filter is used in [9] to compensate for this insensitivity.

3.2.4 Identification metric

The target identification/classification is another important aspect that also needs to be considered by the data fusion system in order to produce the complete tactical picture required by the subsequent C^2 processes.

Identification of potentially hostile targets is accomplished using visual, electronic, oral, or printing devices. Identification procedures are critical to prevent fratricide. Identification, Friend or Foe (IFF) interrogators are used to electronically challenge target transponders to determine whether the targets are friendly or unknown. Identification sources include cooperative sensors (*e.g.*, IFF), non-cooperative sensors (*e.g.*, electronic surveillance), procedural

methods (*e.g.*, air corridor), and indirect sensors (*e.g.*, various intelligence sources).

Such identification/classification processing must accurately integrate the distinguishing attributes of the targets actually observed, and provide estimates of their identity/class/type. The discrete nature of the state/outcome/action space associated with such identification and/or classification problems imposes some restrictions/limitations in the definition of metric.

3.2.4.1 Fisher matrix

In the case of identity fusion that chooses between different hypotheses, the Fisher information is not defined due to the discrete state/outcome space.

3.2.4.2 Entropy change

As for the tracking (*i.e.*, continuous) case, the entropy change can be used as a management basis for the identification problem. This metric is however defined differently to take into consideration the discrete nature of the state space. Hence, the entropy change is defined, in the discrete case, as

$$h = E\Big[-\ln(\boldsymbol{P}(\Theta))\Big] \tag{12}$$

$$= -\sum_{H\in\Theta} \boldsymbol{P}(H)\ln(\boldsymbol{P}(H)) \tag{13}$$

while the associated information measure is given by

$$i = -h \tag{14}$$

$$= \sum_{H\in\Theta} \boldsymbol{P}(H)\ln(\boldsymbol{P}(H)) \tag{15}$$

3.2.4.3 Discrimination gain

The discrimination gain can also be used in discrete cases such as in the identification problem. It was used as a metric in [13, 28] for the problem of classification of both single and multi-sensor situations. The proposed strategy selects the sensor action that maximizes the discrimination, (or cross-entropy) D of the *a posteriori* probability $\boldsymbol{P}(\Theta|\boldsymbol{z}_i)$, given the *a priori* distribution $\boldsymbol{P}(\Theta)$. This is defined by

$$D(\boldsymbol{z}_i) = \sum_{j=1}^{N} \boldsymbol{P}(H_j|\boldsymbol{z}_i)\ln\frac{\boldsymbol{P}(H_j|\boldsymbol{z}_i)}{\boldsymbol{P}_j} \tag{16}$$

Maximizing the discrimination, between the prior and posterior probabilities, means that as much information as possible has been added by the selected action.

3.2.4.4 *Distinguishing the likeliest hypotheses*

Another interesting approach when dealing with identification and/or classification (*i.e.*, discrete space) problems, consists in selecting the sensor action that discriminates the two most likely hypotheses H_j and H_k the best. At each time period, the other (than the two most likely) hypotheses are ignored in the decision process.

With such a formulation, the objective is, given a set of possible hypotheses, to find the sensor action that maximizes the difference

$$z_i^\star = \arg\max_{z_i} \left| P(z_i|P(H_j)) - P(z_i|P(H_k)) \right| \tag{17}$$

where

$$P(H_j) = \max_{H_i \in \Theta} P(H_i) \tag{18}$$

$$P(H_k) = \max_{H_i \in \{\Theta \backslash P(H_j)\}} P(H_i) \tag{19}$$

Note that no calculation of the a posteriori probabilities is needed for the action selection to be performed.

3.3 Action selection

Given the goal specifications, the environment changes and performance measures, the core of the sensor management and control problem amounts to selecting the appropriate course of action. To meet the specifications, the management system should, in its action selection process, be able to reason and make commitments on the environment changes (*i.e.*, reactive planning) and commitments on revised goals (*i.e.*, deliberative planning).

Depending on the underlying problem and the model adopted, there are different techniques for action selection. As discussed previously, the management goal depends upon how the problem is formulated. We distinguish mainly two different objectives that are:

1. maintain the discrepancy between the measured, or estimated, current performance and the desired one within some fixed bound, if the problem is modeled as a control one. This discrepancy (or error) measures how the system being considered is behaving with respect to the specified level of performance.

2. minimize (or maximize) the selected objective functional or the expected utility function, if the problem is posed as an optimization one or a decision one, respectively.

3.3.1 Control theory

Control theory is relevant to the design and the analysis of dynamic systems, especially those that have to operate in a closed-loop mode (*i.e.*, make use of feedback). The action selection problem defined above is the essence of the control design that consists in selecting the action $\boldsymbol{u}$ for a process $\boldsymbol{P}$ so that its output $\boldsymbol{y}$ follows the desired specifications $\boldsymbol{r}$, while not requiring too much control effort (time/resource consumption). A more realistic requirement is that the discrepancy between the process output $\boldsymbol{y}$ and specification $\boldsymbol{r}$ remains within some fixed bound $\boldsymbol{B}$, that is,

$$\|\boldsymbol{y} - \boldsymbol{r}\| \leq \boldsymbol{B} \tag{20}$$

When no control is used, the system configuration is selected at the time of design, and remains fixed throughout the system lifetime. When control is used, there are two sources for its activation. These are the goal modifications and relevant environmental changes, each one corresponding to a different control strategy. Feedforward control is concerned with the goal changes, while feedback control handles changes in the environment. Feedforward strategy represents the simplest form of control, and is also known as the open-loop strategy (see Figure 9). The calculation of the control law $\boldsymbol{u}$ is based only on the inputs of the process, that is, the setpoint or the goal $\boldsymbol{r}$ and the control constraint $\boldsymbol{d}_u$.

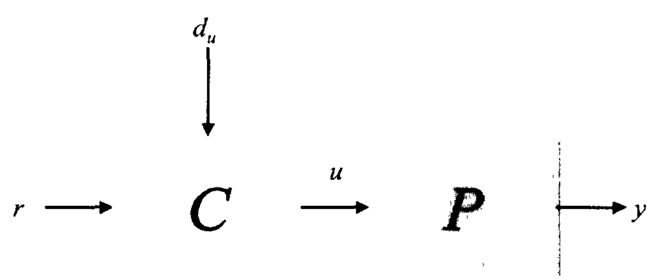


Figure 9: *Feedforward control*

The role of such a control scheme is to ensure that the controlled variable follows changes in the specification, when it is assumed that there is no change in the environment state. In control theory terminology, this is referred

to as the setpoint-tracking problem. This corresponds to the purely deliberative planning model in Artificial Intelligence (AI) terminology where, based on its specification/environment model, an agent plans its actions ahead of time to achieve the goals.

Note that in a static, well-known or entirely predictable environment, the feedforward strategy suffices alone to achieve the control goals. In complex environments, and according to the adaptive system theory, outcomes are however unpredictable. Therefore, the purely deliberative planning model is rather a paradox, if not an aberration. For a system that evolves in a complex environment, it is difficult for its designer to predict and envisage all the changing situations the system will encounter and have to handle.

To maintain an acceptable level of performance, and/or improve it, the controller must be able to react to changes in its environment. Such a behavior is not achievable with the open-loop control, and the feedback strategy thus becomes necessary. In this case, the output y of the process is fed back to the controller. The latter use it, together with the setpoint r, to modify the operating mode of the process. Figure 10 illustrates the feedback control strategy.

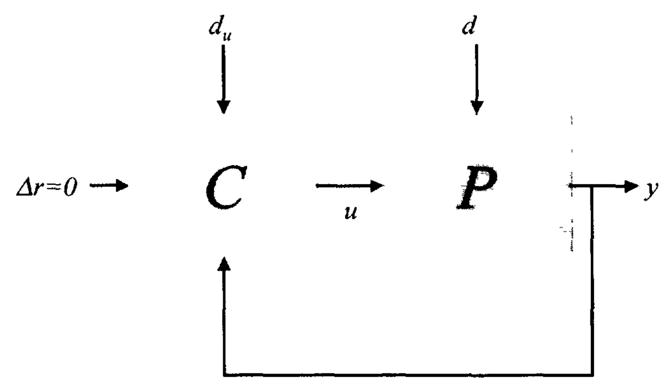


Figure 10: *Feedback control*

Control theory allows, under some conditions (*i.e.*, linearity condition), treating separately the problems of a variable environment with constant specifications and that of variable specifications within a constant environment. These feedback and feedforward control models offer a set of vocabularies to describe runtime behavior in any adaptive system. The design challenge for such systems is to develop ways to combine the feedforward and feedback components of the control, and integrate them in a tightly coupled fashion. Ideally, the adaptive system should consist of both components integrated. This combination of feedforward and feedback models allows

tackling the more general class of variable specifications within a variable environment.

For all of the above described situations, a model M is required to represent the approximate mapping from the control space u to the performance space y. This model defines what is thought of to be the process dynamics, and it may not be accurately known; we then talk about parametric uncertainties. The existence of such a mathematical model M that provides a sufficiently accurate approximation of the process dynamics is one of the main limiting factors in the application of control theory to complex systems. Except for the servo-control level discussed previously, sensor management represents one of such problems where mathematical models are not so easy to obtain, when they even exist.

Hence, for sensor management, and to some extent, control theory only provides a structured framework for the characterization of the underlying problem. Nonetheless, some control-theory based solutions to the sensor management problem have been reported in the literature. [29] and [30] have applied automatic control theory to the problem of sensor scheduling. [6] and [7] use the notion of the covariance control to keep the discrepancy between the desired covariance matrix and the estimated matrix within some bound. [31] handles the sensor/target allocation problem as an optimal control one.

3.3.2 Optimization

Optimization-based algorithms are among the techniques that have been most often applied to the sensor management problem. Besides the previously discussed linear programming-based solutions [8, 25], non-linear optimization techniques have also been used. Such techniques often model the sensor management and control problem as a Markov decision process.

Recall that markovian systems are those systems whose transition functions depend only on the immediately preceding state and action, rather than all the history of the system. Therefore, the state x_{k+1} at time instant t_{k+1} of such systems will depend only on the state x_k at time instant t_k and the action input u_k at time instant t_k

$$x_{k+1} = f(x_k, u_k, w_k, t_k) \tag{21}$$

where w_k is a random variable that reflects the incomplete predictability of the system state. At each time period, the process is in a given state x_k and the decision-maker is faced with a set of action alternatives. Associated with states and actions is a cost function $g(x_k, u_k)$ derived from some metric. The four components of a Markov decision process model are:

1. a set of states : this is the set of possible states of the systems given the initial state and the set of all admissible actions.

2. a set of actions : that represents the set of all possible alternatives (actions) one can choose from.
3. a transition function : this defines how the future state of the system will evolve from its current state under the effect of the actions.
4. an immediate reward function: this measures the immediate value of each action given the state.

The solution to a Markov decision process is called a policy that simply specifies the best action to take for each state.

There are often a number of different alternatives (actions) to choose among when confronted with such an optimization problem. One-step-ahead (or myopic) approaches consider only the immediate effects of the selected actions. Sometimes actions with poor immediate effects can have better long-term ramifications. The action that makes the right tradeoffs between the immediate rewards and the future gains might represent the best possible solution. Solving such Markov decision processes is the approach that may help in modeling and reasoning about the multi-stage decision problems, and there are a number of algorithms that allow automating this solution. Among them, the dynamic programming approach has witnessed much interest from the sensor management community. Dynamic programming refers to a collection of algorithms that can be used to compute optimal policies given a perfect model of the environment as a Markov decision process. The most widely used version of dynamic programming depends on a recursive algorithm that determines the minimum costs based on the final state and works backwards.

[32] describes the management process as a general Markov decision process, which can be solved by dynamic programming. To avoid a possible combinatorial explosion, the author proposed using reinforcement learning as an approximate approach to dynamic programming. [11] also use a dynamic programming-based approach to predict the effects of future sensor management policies. In [14], dynamic programming is applied to the scheduling of multi-mode sensors in the problem of classification of multiple unknown objects. The problem is formulated as Partially Observed Markov Decision Problem (POMDP) and Lagrange relaxation is used to decouple the multi-object problem into many single-object problems. Stochastic dynamic programming is also used in [33] to tackle sensor management as a sequential decision problem.

3.3.3 Decision theory

The sensor management problem is often presented as a decision one. The correctness and optimality of the result, namely action, hinges on the

"rationality" of the decision-making process that prescribes the sensing actions. Although there are a wide variety of contexts in decision making, all decision-making problems have the three following elements

1. the set of decisions (or strategies/actions) available to the decision maker,
2. the set of possible outcomes and the probabilities of these outcomes,
3. a value model (utility) that prescribes results for the various combinations of decisions and outcomes.

Once these elements are known, the decision maker can find an "optimal" decision. Solving such a decision problem can be done efficiently using graphical methods such as decision trees (Figure 7) or influence diagrams.

With respect to sensor management, since the sensor allocation problem can be regarded as an information gathering problem, an intuitive basis for making decisions leading to the best sensing actions is a consideration of the value of the information obtained by these sensing actions. Using the utility theory terminology, sensor management would be reformulated as the definition of a utility function $U(a_i, \boldsymbol{x}_j)$, to evaluate the gain in taking an action a_i, given the environment state $\boldsymbol{x}_j$, and the cost c_i associated with the action. The average utility of performing an action a_i (*i.e.*, the expected utility) is defined as

$$E\Big[U(a_i)\Big] = \sum_{j=1}^{J} P(\boldsymbol{x}_j|a_i)U(a_i, c_i, \boldsymbol{x}_j) \tag{22}$$

where J is the cardinality of the state space. The optimal sensing action a^* is the one that maximizes the expected utility, and is given by the Bayes' decision rule

$$a^* = \arg\max_{i=1}^{I} E\Big[U(a_i)\Big] \tag{23}$$

with I being the dimensionality of the decision space. This ensures that the sensing action that yields the highest utility in average is chosen. An alternative approach to such a Bayesian decision analysis consists in choosing the action a^* that maximizes the worst case. This is rather a conservative approach.

The utility theory may provide a convenient framework where a measure of the importance of the actions can be established. As discussed in Section 3.2, different utility functions are appropriate, depending on the underlying problem. When the goal of sensor management reduces to gathering information, the utility metrics are well defined by the mathematical background of Information theory (*e.g.*, Fisher matrix, entropy, etc.). For higher-level objectives, more complex and less rigorous theories must be used.

As argued by [34], a utility function can always be found, as long as the desired behavior of the controlled system is rational.

[35] uses the utility theory to develop a decision theoretic sensor management architecture. [36] use a decision theoretic approach, based on the Bayesian belief networks, to develop a sensor management system for mobile robots. Blackman proposed, in [15], a sensor/target assignation strategy based on utility theory. Given a candidate sensor/target assignation, models of the sensors are used to predict their performance. The sensor management module selects then the action that maximizes the expected gain in utility. The latter is defined as the marginal utility, which represents the difference between the current utility and the expected one.

Utility theory is also used, in [37], to determine the best allocation of the resources of ESA (Electronically Scanned Array) radar for searching, tracking and identifying tasks for the multi-target tracking. This work was one of the precursors of all modern sensor management. The radar is allocated to the task with the largest marginal utility. The computation of such a utility takes into account the costs of identification decisions and the accuracy of the tracking. In [37], three different marginal utility functions were used

1. Track update utility, which is based on track accuracy.
2. Search utility that is based on detection probability.
3. Track ID utility, which is based on classification accuracy.

Using some independence assumptions, these utility functions are aggregated, in a later stage, into a unique function that serves as an action selection basis. These assumptions represent however the main weakness of the proposed approach, since such an independence is rarely guaranteed in practice.

3.3.4 Artificial intelligence

Even though most of the reported solutions use one or another of the above described approaches, other techniques, mainly inspired by the work of the artificial intelligence community, have also been applied to the sensor management problem. Hence, [38, 39] use an expert system to tackle the pairing problem for Air-to-Air Attack Management (A^3M), for Beyond Visual Range (BVR) detection, track, identification, attack and missile guidance on multiple targets. The permissible pairing sensor/target uses a Boolean matrix, whose construction is based on the availability of each sensor and its capability to perform the corresponding tracking task. They defined the ability in terms of the availability (failure/busyness) and the capability of the sensor.

Similarly, Popoli & Blackman used an expert system, in [40, 41], to tackle the sensor management problem. This system combines a simple "IF-THEN"

knowledge base and an inexact inference engine, based on fuzzy set theory. Basic or root concepts are encoded as membership functions, while composite (higher order) concepts are inferred using the logical connectives $\bigcup$, $\bigcap$ and $\neg$. An expert system, which represents one of the first applications of Artificial Intelligence to be reported in the context of sensor management, is also used in [42]. An expansion of this work is reported in [43], where a combination of information from multiple agents, through a blackboard architecture, is used. Other expert systems are reported in [44, 45], while in [46] a back propagation neural network is combined with parallel Kalman filters to track maneuvering targets.

3.4 Other functionalities

Even though the goal specification, the performance evaluation and action selection represent the core of the sensor management problem (and of any control and planning problem, in general), other functionalities are also required. Some of the most important functionalities are listed below.

3.4.1 Action execution

Sensor management needs a configuration modification functionality that provides the system with the means for the execution of selected actions. The manager should be able to insert the change into the existing system with minimal disruption to existing behaviors.

3.4.2 Evaluation of the control performance

Another important aspect of any control/management/planning problem is the evaluation of the control performance. This is different from the performance evaluation discussed so far and which is rather concerned with the open-loop behavior of the target system. The evaluation of the management performance concerns the behavior of the closed-loop system (under the action of the control). This has as an objective to measure the gain in the performance brought by the management actions.

Some other properties (metric) borrowed from control theory may also provide a general guideline for predicting/measuring the performance of the closed-loop sensor system. Examples of such widely used metric are defined below. Note that control theory may provide tools for predicting the performance of a closed-loop system given that of the corresponding open-loop system.

3.4.2.1 Stability

It is the most important metric when dealing with closed-loop systems. A system is said to be stable if its response to a bounded input is itself bounded by a desirable range. In other words, a loop is said to be stable when small changes in the specification/environment lead to small changes in the performance[1]. Even when the process is open-loop stable, using feedback control may render the process unstable. Different factors may lead the loop to instability. In the sensor management context, an example is given by the "data looping" condition, where information generated by a given management agent may be returned to it, through the feedback path, as a new extra information.

3.4.2.2 Robustness

For controlled systems it may not be sufficient to be nominally stable (for a given configuration/model). They have to remain stable even if the system/conditions are different from the intended ones in some measured ways.

3.4.2.3 Response time

When switching from one configuration/mode to another, it may be important to measure how long the system will take to reach its new desired state. The response time (or transient time) measures such a transient response of the system, that is the time it takes the system to transit from one stable state to another.

[1]This is only a special case of the stability property, which is known as the Bounded In Bounded Out (BIBO) stability.

4. Application : Adaptive sensor allocation

In this chapter, the problem of sensor allocation in the tracking context, also known as adaptive tracking, will be considered. Adaptive tracking is the problem that has most often been studied by the sensor management community. Presented as a control, an optimization or a decision problem, the objective mostly remains the same, *i.e.*, to reduce, at the lowest cost possible, the uncertainty (*e.g.*, the error covariance matrix) in the kinematical information about the tracked targets. However, the used metric and problem formulation differ from one solution to another. It is worth noting that the objective, at this stage, is not to seek the best formulation of and solution to the problem, but rather to demonstrate the benefit that can be gained by the use of advanced management concepts.

4.1 Problem statement

The case of one or more sensors tracking a set of distinct targets will be considered. Each one of these sensors is assumed to have different performances and utilization costs. An interesting management concept to be illustrated is the dynamic allocation of the sensor(s) against the target(s). The selected allocation policy will be the one that minimizes some objective function. The latter may, for instance, combine in some way the performance and cost associated with the different sensor/target pairings. Five scenarios, that depend on the number of the targets and the sensors considered, will be presented:

1. One sensor against one target.
2. One sensor against two targets with no priority.
3. Three sensors against one target.
4. Three sensors against two targets with no priority.
5. Three sensors against two externally prioritized targets.

4.2 Dynamical model

The tracked targets are assumed to be moving in 2D space, where the input may change unforeseeably, and therefore is modeled as a random variable. The state to be estimated is therefore composed of the target's coordinates that define the state vector as follows

$$\boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{24}$$

The dynamical equations of such targets can be expressed as

$$\boldsymbol{x}_{k+1} = \boldsymbol{F}\boldsymbol{x}_k + \boldsymbol{\Gamma}\boldsymbol{v}_k \tag{25}$$

where v is a random variable that reflects the unforeseeable variation of the dynamics and/or the modeling errors. The state transition matrix is given by

$$F = \begin{bmatrix} 1.1 & 0 \\ 0 & .98 \end{bmatrix} \tag{26}$$

Note that for simplicity purposes, a linear model is assumed. The use of non-linear dynamical equations should not affect the management policy. The process noise covariance matrix is given by

$$Q = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \tag{27}$$

The observation equations are expressed as

$$z_{i_k} = H_i x_k + w_k \tag{28}$$

where k is the observation time, i is the number of the sensor and H_i is the observation matrix, that is given for each of the three considered sensors by

$$H_1 = \begin{bmatrix} 1.5 & 0 \end{bmatrix} \tag{29}$$
$$H_2 = \begin{bmatrix} 0 & 1.5 \end{bmatrix} \tag{30}$$
$$H_3 = \begin{bmatrix} 1.2 & 0 \end{bmatrix} \tag{31}$$

The measurement noise w is assumed to be the same for the three sensors, with a covariance matrix R. Also, associated with each sensor there is an utilization cost

$$c_1 = 6.30 \tag{32}$$
$$c_2 = 6.30 \tag{33}$$
$$c_3 = 5.85 \tag{34}$$

4.3 Objective function

Since the primary goal of any tracking system is to reduce the uncertainty in the target's kinematic information, a metric is required to quantify the information that would be gained by the sensing actions. A natural metric for measuring the tracking operation performance might be based on the error covariance matrix $\hat{P}_{k+1|k+1}$ maintained by the Kalman filter. The Kalman filter [18] is often used for the estimation (fusion) of the target's state vector. One form of its recursive algorithm is given by

$$\hat{P}^{-1}_{k+1|k+1} = \left[F\hat{P}_{k|k}F^T + Q\right]^{-1} + H_i^T R^{-1} H_i \tag{35}$$

$$\hat{P}^{-1}_{k+1|k+1}\hat{x}_{k+1|k+1} = \left[F\hat{P}_{k|k}F^T + Q\right]^{-1} F\hat{x}_{k|k} + H_i^T R^{-1} y_{i_{k+1}} \tag{36}$$

The trace, the determinant or other more sophisticated norms of $\hat{P}_{k+1|k+1}$ may be used to obtain a scalar metric. In the remainder, the trace will be used. Minimizing the trace

of $\hat{P}_{k+1|k+1}$ is equivalent to reducing the sum of the variances of the different variables in the state vector. To take into consideration the utilization cost, the following objective function will be considered

$$\min_{a} \left[\text{trace}\,(\hat{P}_{k+1|k+1}) + \lambda a c \right] \tag{37}$$

where λ is a weighting factor, a is the action set, and c the sensing cost.

4.4 Results and discussion

The above equations give the general form of the objective function and the dynamical equations that act as constraints in the optimization formulation. The exact expressions depend heavily on the elements of the scenario. In the following, the expressions for the above-mentioned five scenarios will be given and the results discussed.

4.4.1 One sensor against one target

The first case to be considered is the one of one sensor tracking one target. The problem consists here in choosing, at each time period, between the two following alternatives

1. No measurement ($a = 0$), *i.e.*, time alignment only.
2. Measurement ($a = 1$), *i.e.*, time alignment followed by a state update.

This decision will be made taking into consideration the cost c of the sensing action (*i.e.*, the use of the unique sensor). This problem can be regarded as the one of an adaptive selection of the track's update rate. In the case of one against one, two static policies are possible

1. the update rate is maximal (*i.e.*, $1/1$) all the time, which provides the best performance but results in a high cost.
2. no update (prediction only) all the time, which results is an unboundedly growing estimation error.

The management objective here is to design an adaptive policy that makes the best trade-off between the two above-mentioned extreme solutions. The goal is to reduce the sensing cost (by reducing the update frequency) while keeping the estimation error small. Such an optimization problem can be formulated as

$$\min_{a} \left[\text{trace}\,(\hat{P}_{k+1|k+1}) + \lambda a c \right] \tag{38}$$

To simplify the notation, the subscribe $(k+1|k+1)$ will be dropped from the expression of the covariance matrix $\hat{P}_{k+1|k+1}$, that is $\hat{P} \equiv \hat{P}_{k+1|k+1}$. The

above optimization problem is subject to the constraint

$$\hat{P}^{-1} = \left[F\hat{P}_{k|k}F^T + Q\right]^{-1} + aH^TR^{-1}H \tag{39}$$

where H is the observation matrix of the considered sensor. The other constraints are

$$a \in \{0,1\} \tag{40}$$

$$0 \leq \lambda \leq 1 \tag{41}$$

The optimization results are given by Figures 11 to 13. Figure 11 shows the optimal update rate (*i.e*, $1/3$) that takes into consideration both the track quality and measurement cost.

The optimal update frequency is the ratio of the width of the red bars over the width of the white bars plus the width of the red bars. As shown in Figure 12, the adaptive update strategy yields the best trade-off.

The results compare the adaptive update strategy with all the possible static ones (*i.e.*, 3/3 or 0/3 update in the case of a single sensor). Note that the zero update strategy (*i.e.*, that only makes prediction) leads the estimation process to divergence. Since no information on the target is gathered from the environment, the error covariance matrix will continue to grow unboundedly. Figure 13 gives the same comparison but taking into consideration only the performance aspect. The costs are assumed null. In this case, it is clear that the static strategy (*i.e.*, $1/1$) yields the best performance. The sensing action costing nothing, the more information we gather, the better the result will be.

4.4.2 One sensor against two targets

In the case of one sensor tracking two targets, the problem consists in choosing, at each time period, between the three following alternatives

1. Time alignment only, for both targets ($a_1 = a_2 = 0$)
2. Time alignment followed by a state update for the track of target 1 ($a_1 = 1$) and time alignment only for target 2 ($a_2 = 0$).
3. Time alignment followed by a state update for the track of target 2 ($a_2 = 1$) and time alignment only for target 1 ($a_1 = 0$).

while taking into account the cost c of the sensing action. It assumed that the two targets have equal priorities. This problem is similar to the previous one, where an optimal update rate is to be calculated. The difference lies mainly in the fact that the system must simultaneously track two targets with only one sensor. In order to minimize the overall uncertainty in the information about

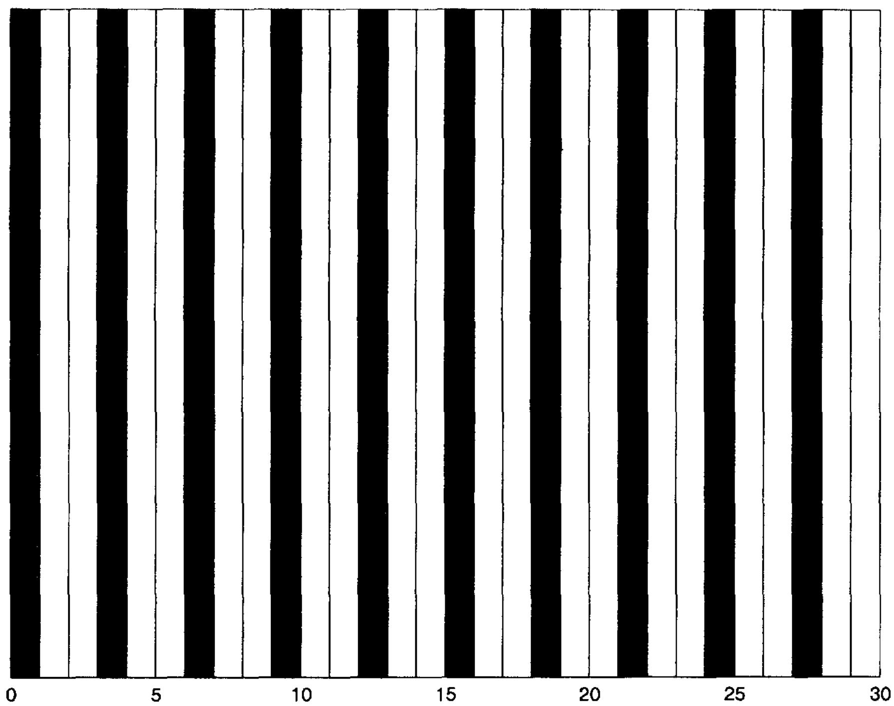


Figure 11: *Update rate for the case of 1 sensor against 1 target*

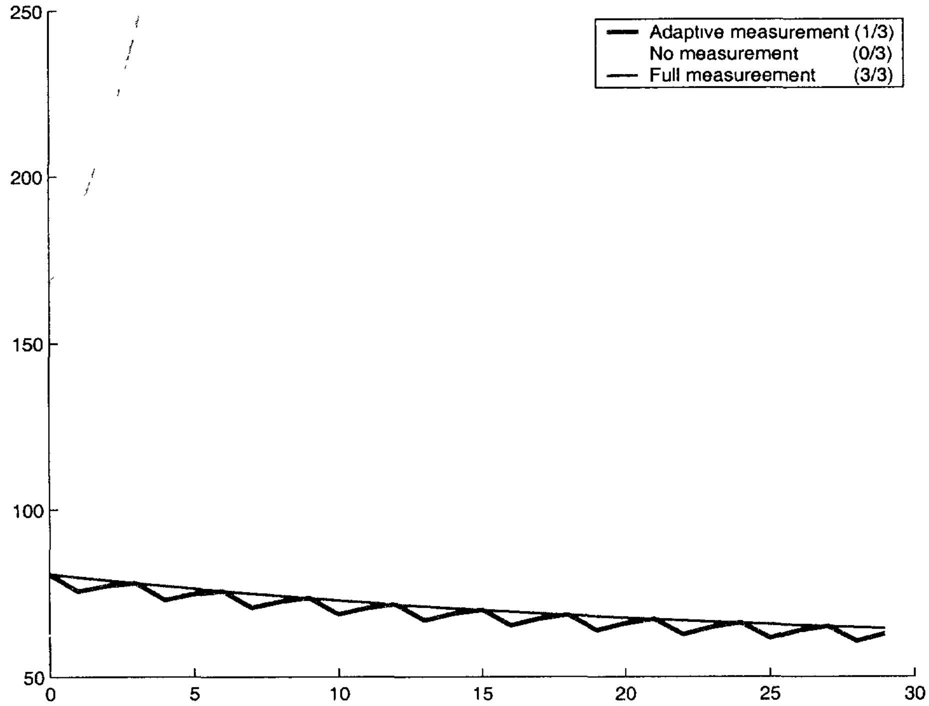


Figure 12: *Trade-off cost/performance foı the case of 1 sensor agaınst 1 target*

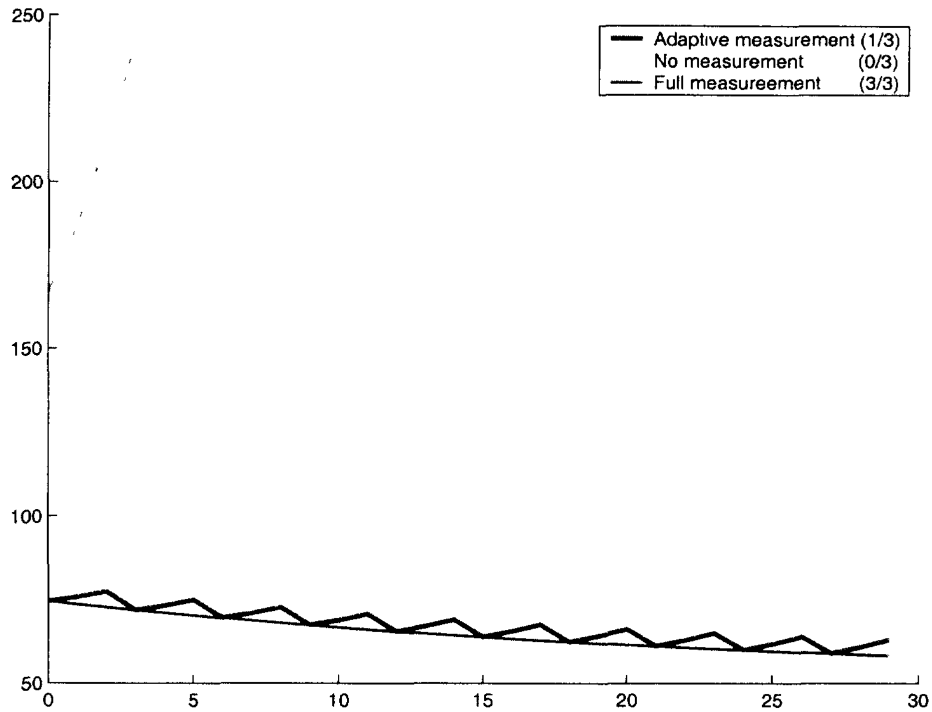


Figure 13: *Performance only for the case of 1 sensor against 1 target*

the two targets, some compromise needs to be found. In this case, decision basis metrics may, for instance, be given by the sum of the traces of the two error covariance matrices $\hat{P}_1$ and $\hat{P}_2$. The optimization problem can be formulated as

$$\min_{a_1, a_2} \left[\text{trace}\,(\hat{P}_1) + \text{trace}\,(\hat{P}_2) + \lambda(a_1 + a_2)c \right] \tag{42}$$

subject to

$$\hat{P}_1^{-1} = \left[F\hat{P}_{1_{k|k}}F^T + Q \right]^{-1} + a_1 H^T R^{-1} H \tag{43}$$

$$\hat{P}_2^{-1} = \left[F\hat{P}_{2_{k|k}}F^T + Q \right]^{-1} + a_2 H^T R^{-1} H \tag{44}$$

and

$$a_1 + a_2 \leq 1 \tag{45}$$

$$a_1 \in \{0, 1\} \tag{46}$$

$$a_2 \in \{0, 1\} \tag{47}$$

$$0 \leq \lambda \leq 1 \tag{48}$$

The results are given in Figures 14 to 17. Since the targets are of the same priority, their optimal update rates are equal (*i.e.*, 1/3) and the two are equal to the update rate of the previous section (Figure 11).

Note that for this scenario, all of the static allocation policies lead to divergence. The sensor must be shared between the two targets to guarantee that the two error covariance matrices remain bounded. The optimal sharing policy is the one that minimizes the above-given objective function.

4.4.3 Three sensors against one target

The case of three sensors against one target is now considered. The problem consists in choosing, for the target, between a time update only and a time update with measurement, while taking into account the cost of the sensing actions. To consider the case of more than one sensor tracking simultaneously the target, pseudo-sensors [8], which are combinations of sensors, are defined. The number of sensors (either actual or pseudo) is thus equal to $M = 2^S - 1$, where $S = 3$ is the number of the individual (actual) sensors in this case. The optimization problem consists in assigning the M combinations to the target in the way that yields the best trade-off uncertainty/cost. The optimization problem can be formulated as

$$\min_{a_i} \left[\text{trace}\,(\hat{P}) + \lambda \sum_{i=1}^{M} a_i c_i \right] \tag{49}$$

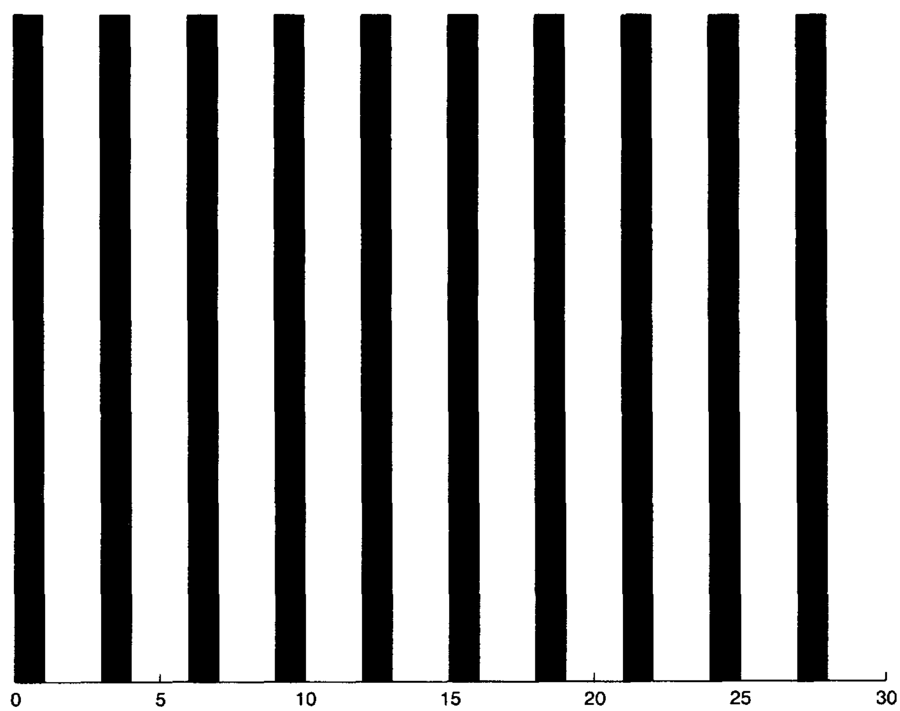


Figure 14: *Update rate for Target 1 for the case of 1 sensor against 2 targets*

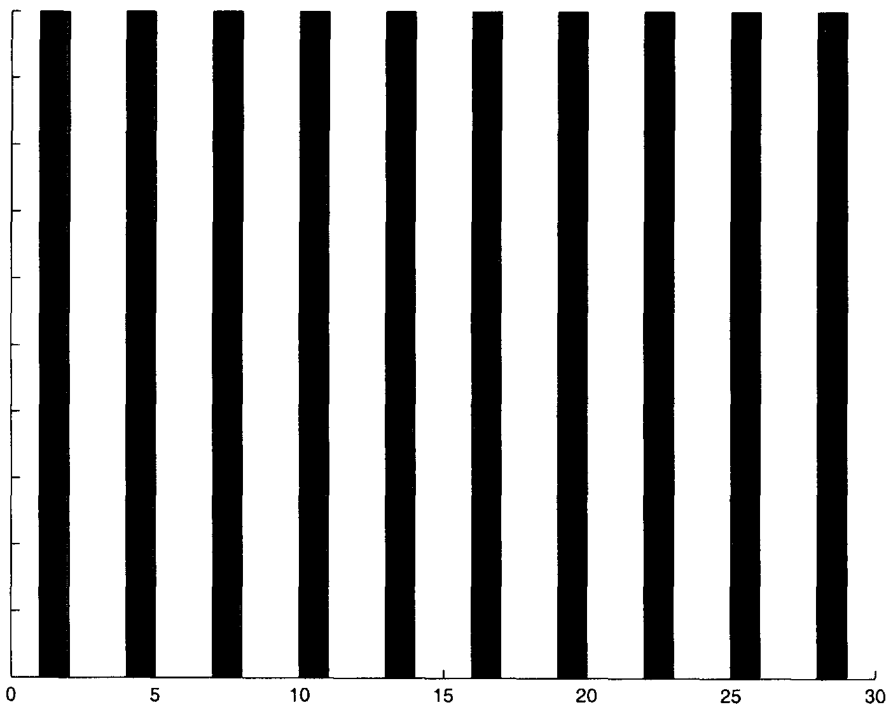


Figure 15: *Update rate for Target 2 for the case of 1 sensor against 2 targets*

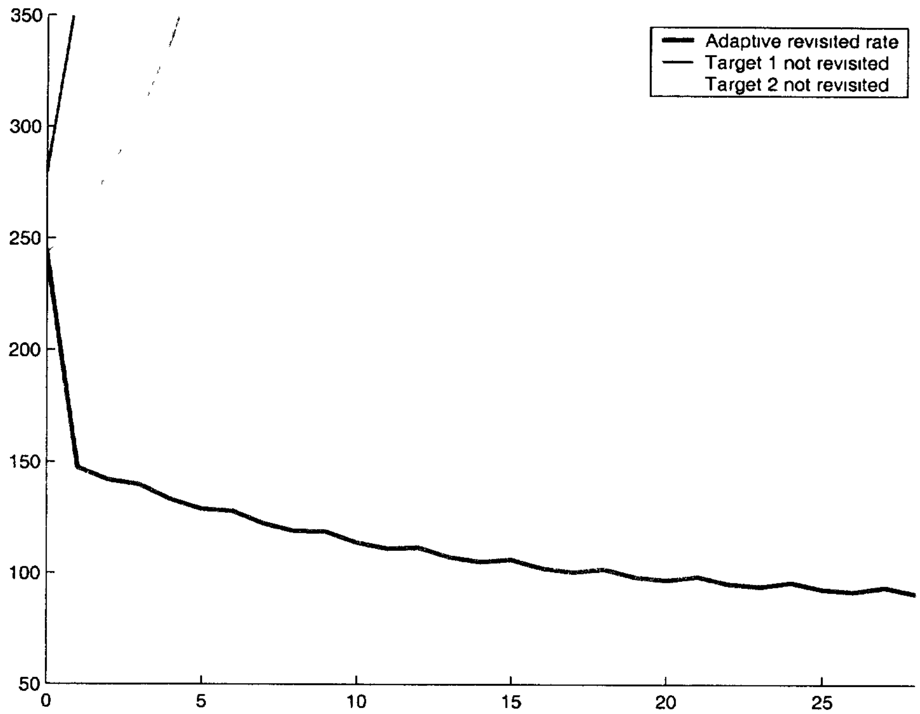


Figure 16: *Trade-off cost/performance for the case of 1 sensor against 2 targets*

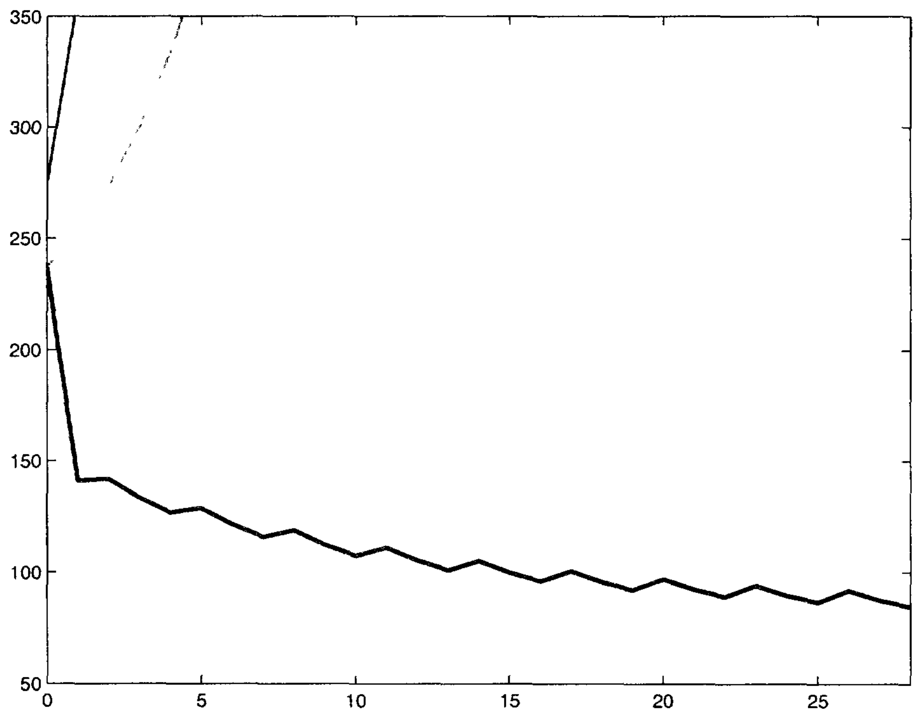


Figure 17: *Performance only for the case of 1 sensor against 2 targets*

subject to

$$\hat{P}^{-1} = \left[F\hat{P}_{k|k}F^T + Q\right]^{-1} + \sum_{i=1}^{M} a_i I_i \tag{50}$$

where the information brought by the sensing action i (*i.e.*, when $a_i = 1$) is given by

$$I_i = \begin{cases} H_i^T R^{-1} H_i, & \text{for} \quad i = 1,3 \\ \sum_{j \in C(a_i)} H_j^T R^{-1} H_j, & \text{for} \quad i > 4 \end{cases} \tag{51}$$

where $C(i)$ is the set of sensors that form the combination i (*e.g.*, $C(6) = \{2,3\}$). The cost of the sensing action i is simply the cumulative sum of the costs of the selected sensors (within a given combination)

$$c_i = \begin{cases} c_i, & \text{for} \quad i = 1,3 \\ \sum_{j \in C(a_i)} c_j, & \text{for} \quad i > 4 \end{cases} \tag{52}$$

The set of constraints is given by

$$\sum_{i=1}^{M} a_i \leq 1 \tag{53}$$

$$a_i \in \{0,1\} \tag{54}$$

$$0 \leq \lambda \leq 1 \tag{55}$$

Figures 18 and 19 show the simulation results for this scenario. Even though several static policies provide a bounded covariance matrix, the adaptive one yields the best trade-off uncertainty/cost. Note also that, since the sensor 3 costs less than the sensor 1, the former is used more often than the latter, even though it is less accurate.

4.4.4 Three sensors against two targets

The last case to be considered is the one of three sensors (and their combinations: $i = 1$ to $2^3 - 1$) tracking two targets. The optimization problem is formulated as follows

$$\min_{(a_{1_i}, a_{2_i})} \left[\beta_1 \text{trace}(\hat{P}_1) + \beta_2 \text{trace}(\hat{P}_2) + \lambda \sum_{i=1}^{M} (a_{1_i} + a_{2_i}) c_i\right] \tag{56}$$

subject to

$$\hat{P}_1^{-1} = \left[F\hat{P}_{1_{k|k}}F^T + Q\right]^{-1} + \sum_{i=1}^{M} a_{1_i} I_i \tag{57}$$

$$\hat{P}_2^{-1} = \left[F\hat{P}_{2_{k|k}}F^T + Q\right]^{-1} + \sum_{i=1}^{M} a_{2_i} I_i \tag{58}$$

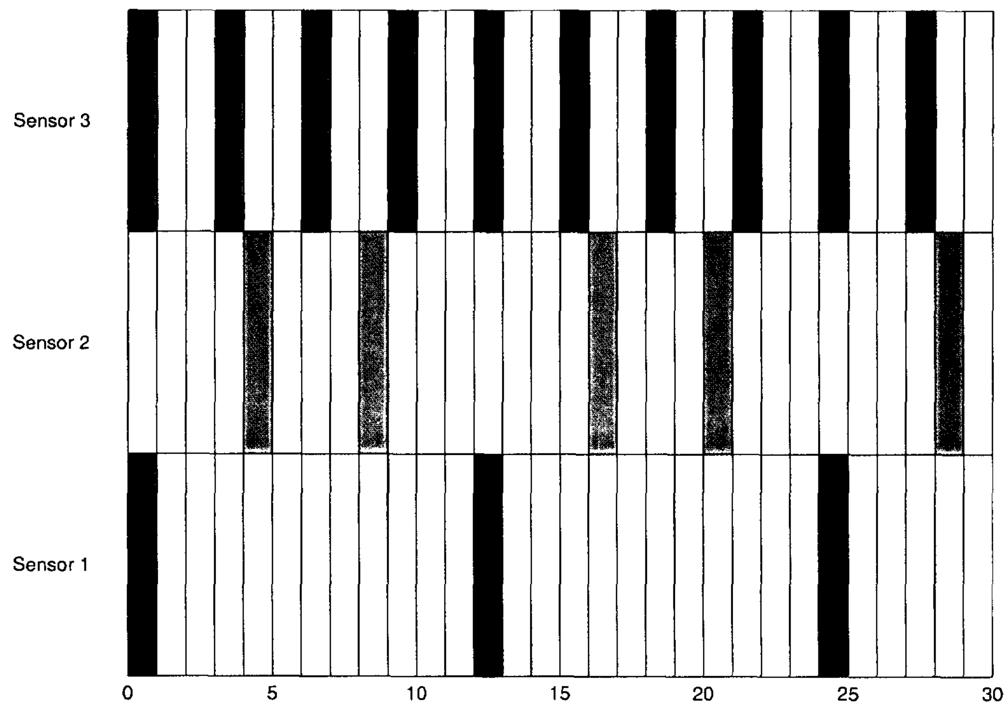


Figure 18: *Sensor allocation and update rates for the case of 3 sensors against 1 target*

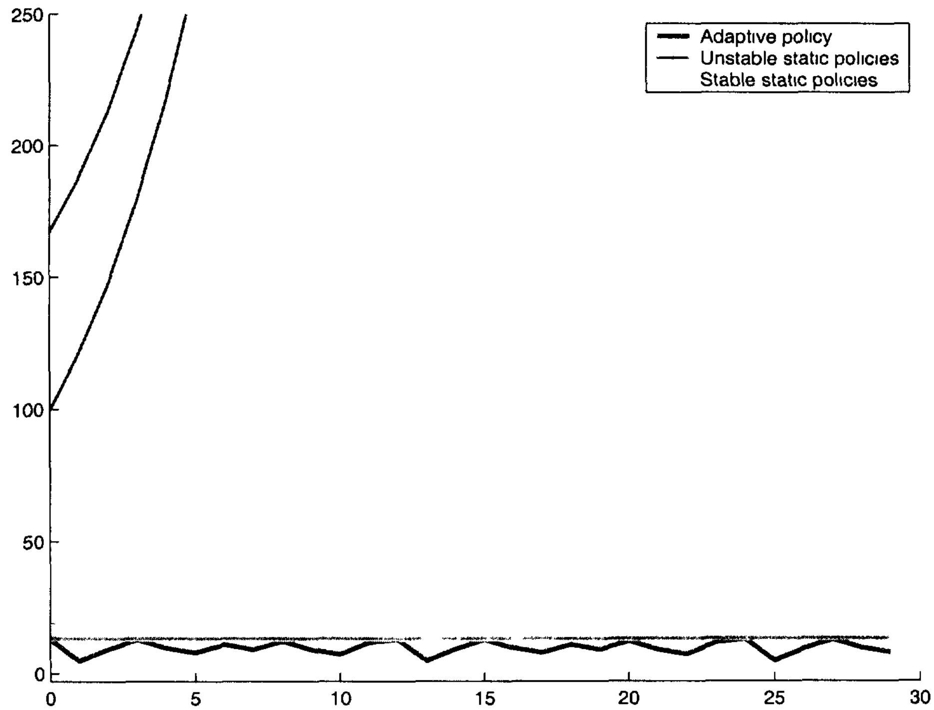


Figure 19: *Trade-off cost/performance for the case of 3 sensors against 1 target*

and

$$\sum_{i=1}^{M} a_{1_i} \leq 1 \tag{59}$$

$$\sum_{i=1}^{M} a_{2_i} \leq 1 \tag{60}$$

$$a_{i_j} \in \{0, 1\} \tag{61}$$

$$0 \leq \lambda \leq 1 \tag{62}$$

To ensure that the same sensor will not be allocated to both targets at the same time, the following constraint is added.

$$C(a_1^*) \cap C(a_2^*) = \emptyset \tag{63}$$

where (a_1^*, a_2^*) is the solution to the above-given optimization problem. In equation (56), β_1 and β_2 represent relative priority factors for targets 1 and 2, respectively. Two situations will be investigated in the following

1. No priority (*i.e.*, $\beta_1 = \beta_2 = 1$) : in this case, the two targets are assumed to be of the same importance.

2. Prioritized targets (*e.g.*, $\beta_1 = .5; \beta_2 = 1$) : in this case target 2 is assumed more important than target 1. Therefore, the revisit rate for target 2 should be higher than target 1's revisit rate.

The optimal update policies for the two above-described situations are given in Figures 20 to 23. It is noticed that when the targets are of the same importance, the attention of the sensors is equally shared between the targets. Except for the time shifts (for each sensor), the update patterns of Figure 20 and Figure 21 are very similar. In the case of prioritized targets, target 2 (see Figure 23) is, as expected, revisited more often than target 1 (see Figure 22).

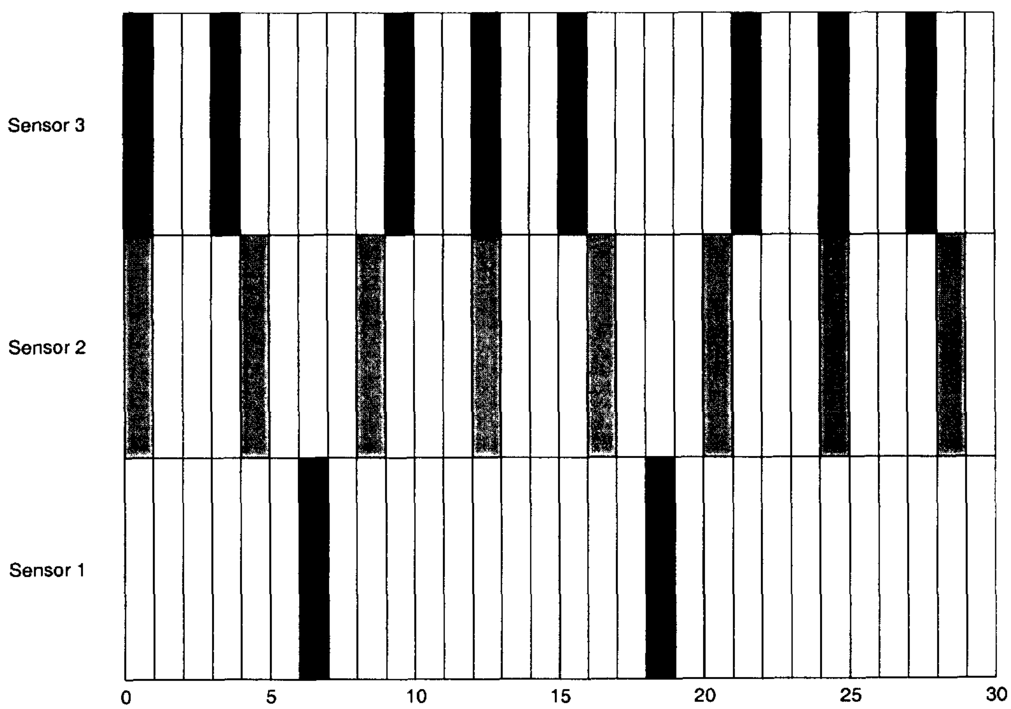


Figure 20: *Update rate for Target 1 for the case of three sensors against two targets (no priorities)*

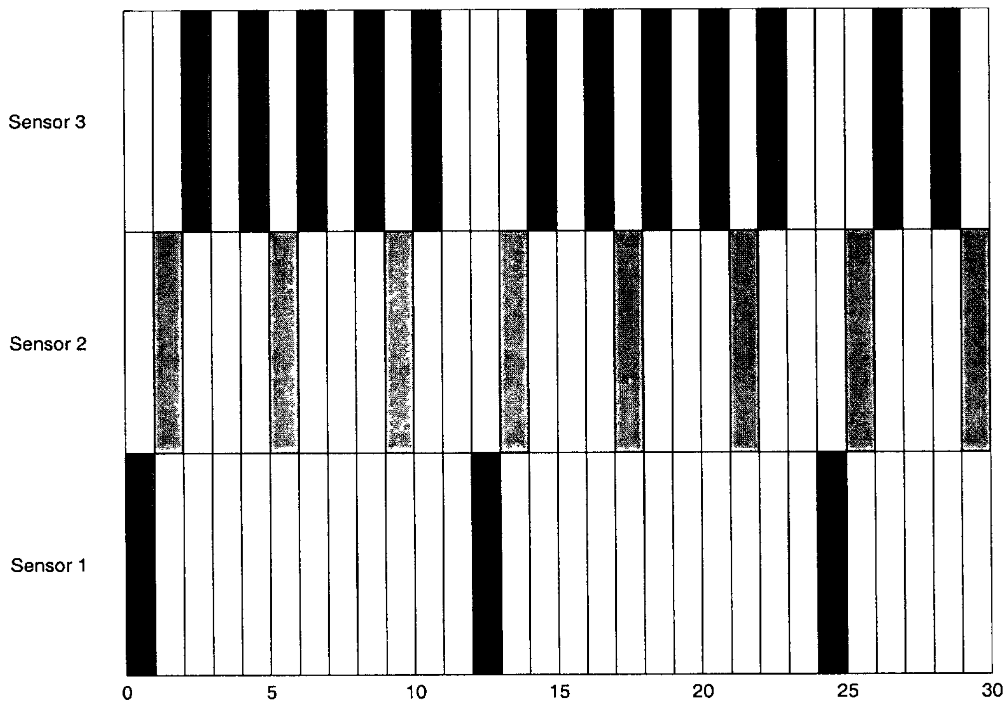


Figure 21: *Update rate for Target 2 for the case of three sensors against two targets (no priorities)*

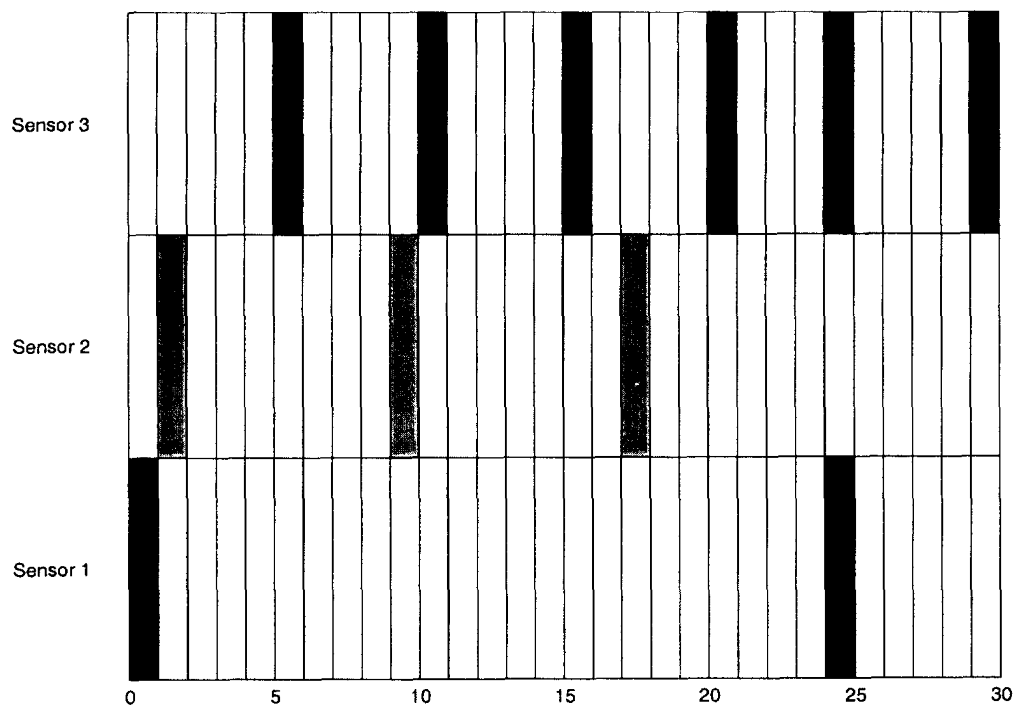


Figure 22: Update rate for Target 1 for the case of three sensors against two externally prioritized targets

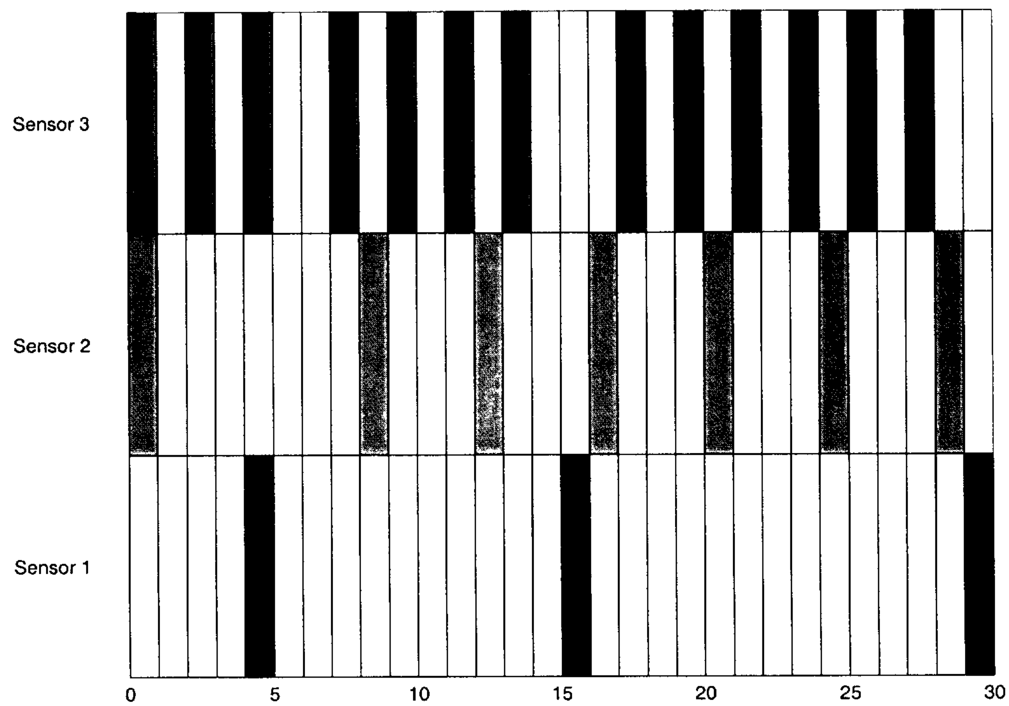


Figure 23: *Update rate for Target 2 for the case of three sensors against two externally prioritized targets*

5. Conclusion

Sensor management has to do with how to best coordinate and organize the use of sensing resources in a manner that synergistically improves the process of data fusion. Based on contextual information, the sensor manager develops options for collecting further information, allocates and directs the sensors towards the achievement of mission goals and/or tunes the parameters for the real-time improvement of the effectiveness of the sensing process.

As can be noticed from the discussion and results of the previous sections, the costly sensing resources can be adaptively managed. Compared with static policies, adaptive management may help reducing the utilization of scarce resources, while keeping the system performance within acceptable bounds. The objective of the reported work was the demonstration of the benefits that can be brought by the closed-loop management of sensors. More elaborate solutions are currently under investigation. They aim at overcoming the relevant limitations of the current solutions, namely concerning

1. The myopic nature of the proposed algorithm. The optimization is performed here on the basis of the immediate effect of the action without taking into consideration the residual effect on the state of the system in the future. To consider the predictive planning issue, models, such as Markov decision process, are being considered.

2. The trace is a relatively simple metric. Other more sophisticated metrics, such as the discrimination gain, might be employed.

3. Finally, to take into consideration maneuvring targets, multiple model-based tracking methods will represent good alternatives to the standard Kalman filter. This problem is thus the estimation issue rather than a management one.

Also, to contrast with the approaches so far reported in the literature and which address sensor management and integration of the fusion levels (*i.e.*, process refinement) separately, we are tackling the sensor management problem within the broader perspective of Situation Analysis (SA). The unified approach in development should allow maximizing the profit that can be gained by sensor management from the contextual information provided by the higher data fusion levels, and vice versa.

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